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Exploration of a Dynamic Lighting Energy Modeling Algorithm for Data Collection Support

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EXPLORATION OF A DYNAMIC LIGHTING ENERGY MODELING ALGORITHM

FOR DATA COLLECTION SUPPORT

by

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of scholarly work in the above mentioned discipline.

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Exploration of a Dynamic Lighting Energy Modeling Algorithm for Data Collection Support

Thesis directed by Professor Gregor P. Henze

[Abstract]

The purpose of this research was to identify appropriate occupancy and lighting energy models for predicting lighting energy use in buildings and use those results to inform data collection recommendations. A first-order inhomogeneous Markov-chain occupancy model was selected to simulate occupancy patterns in single-occupancy offices. A stochastic lighting action model, modified to bring it inline with current research, was used to simulate the interaction of those occupants with their lighting system assuming certain luminous conditions, including the contribution of daylight. Additionally, the lighting control model was expanded to include a range of user types between a true "active" user who acts in a very energy-aggressive manner and a true "passive" user who uses their lighting independent of daylight conditions and with less regard for wasted energy. The combination of these two models was assessed in a sensitivity analysis using both sensitivity index and total sensitivity for each parameter, which allows their contribution to the combined model's variance to be evaluated. It was found that the mobility parameter in the occupancy model contributed most to the model variance, followed closely by the probability of a switch-off action at departure. The switch-on actions, both at arrival and during occupancy, contributed the least to the model's variance. The combination of models was also applied to assess their ability to predict lighting energy use through comparison to deterministic modeling results and sub-metered lighting energy data from an actual building. Based on the results of that validation assessment, it was found that the limitations in

the occupancy model prevented good agreement between measured and predicted

performance. Additional model parameters were proposed for integration into the occupancy

model, and the revised occupancy model was validated against the sub-metered lighting energy

data. The modifications to the occupancy model were found to substantially improve the

accuracy of the predictions compared to the sub-metered data.

DEDICATION

For my family.

ACKNOWLEDGEMENTS

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INTRODUCTION

According to the results of the 2003 Commercial Buildings Energy Consumption Survey (2008), the latest available reliable statistic, lighting was responsible for nearly 38% of the national commercial non-mall building electrical consumption. Lighting, therefore, represents the single largest end-use of electricity in the typical commercial building.

Currently, lighting is regulated through the infrastructure provided in building energy codes. There are multiple energy codes in existence and use in the United States, including the American Society of Heating, Refrigeration and Air-Conditioning Engineer's (ASHRAE) Standard 90.1 for commercial buildings and standard 90.2 for residential buildings, California's Title 24 Part 6, and the International Code Council (ICC's) International Energy Conservation Code (IECC) to name a few. All of these typical building energy codes provide minimum efficiency standards through prescriptive or performance-based approaches. Additionally, all of these energy codes address the actual energy systems, such as heating, cooling and lighting, but also the architectural components that impact the building energy consumption, such as wall and roof insulation, fenestration type and allowable heat loss, and basement configuration. The prescriptive requirements in general provide line-item requirements for each regulated building component, and compliance is demonstrated by illustrating that the efficiency of the specified equipment, component or system meets or exceeds the minimum requirements. The performance requirements are typically based on more advanced simulation methods, and typically provide a maximum allowable annual energy density based on use type that is determined through simulation.

For lighting in particular, systems are generally regulated through a combination of methods. All of the active lighting energy codes reviewed provide mandatory control

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requirements, such as automatic shut-off during hours of non-use. Some of the more advanced

lighting energy codes provide mandatory requirements for more advanced control strategies,

such as daylight-responsive switching or dimming, or occupancy-based controls. The second

part of most current lighting energy codes is the regulation of the allowed lighting power

installed. The method for regulating this is typically by providing a maximum allowable lighting

power density, either applicable to the entire building, or in an application-specific manner.

These lighting power densities address only the installed wattage within the building, and

typically do not include portable lighting equipment which contributes to plug loads.

Additionally, to incentivize more advanced lighting controls, credits are provided in a few codes

which effectively increase the allowable installed lighting power based on the type of extra

controls added. For example, many codes provide an additional lighting power allowance if a

dimming system with pre-set control scenes has been installed in a particular space type.

The main shortfall with the existing lighting energy code infrastructure is that the

regulation is based solely on lighting *power* density. The provided control credits are typically

not equatable to the potential energy savings, but instead are based on conservative estimates of

aggregate cost-effectiveness made by lighting professionals. Regulation of the lighting system

based solely on these installed power densities does nothing for either the end-user or the utility

providing the electricity to be able to evaluate the actual energy and demand impacts, including

time-of-day issues and user interaction.

Purpose

Given the potential impacts of continually refined lighting energy evaluation tools, it has

been a desire within the lighting community to transition toward the regulation, analysis and cost

estimating of lighting energy, instead of lighting power. To do this will require a realistic

consideration of the combined effects of occupancy predictions, the interactions of occupants with lighting controls, the effectiveness of automated controls and rates of overriding, and use and control of daylight delivery and shading systems.

This research effort was intended as a step toward identifying the means by which lighting energy may become a focus of energy prediction, which explicitly meant finding the tools that would be most useful to predict lighting energy use on both space and building scales. For this, an occupancy model, which incorporates the range of human behavior, was first identified and evaluated. A separate lighting action model, which takes occupancy patterns and integrates a second level of irregularity of human behavior, was then selected and reviewed for its potential use and potential modifications. The combination of these models was then explored in terms of understanding the impact of the various free variables from the combined model.

Throughout this process, a desired focus was to understand and quantify the limitations of the models, since it was expressly known that the available models would be limited in their applicable scope. Since the purpose of this effort was to support an overall transition to lighting energy use rather than power densities across all building types and uses, it is important to explicitly identify the shortfalls of each model and to identify ways in which the models can be expanded to include additional possible scope. Therefore, the final purpose of this effort was to use the information gathered from reviewing the models to inform data collection recommendations, which are intended to be used to inform broad-scale collection efforts which will create the knowledgebase necessary to expand and validate the models.

Document Organization

This document is organized to present the process used. First, background information is presented to provide context for model selection and expansion. Next, a description of the initial modeling effort is presented, including the processes for expanding the model and performing the initial comparison, sensitivity analysis and initial validation. The results of that initial effort are then presented and the implications of those results explored. That is followed by a description of the expanded occupancy model and the process used to expand that model, which was then used to re-validate the combined models against the presented subject building data, and the results of that validation are then presented and discussed. Additionally, the process for evaluating the daylighting algorithm is explored and the results of that effort are presented. Finally, the overall results are discussed with respect to their implications on future data collection efforts.

BACKGROUND RESEARCH

Understanding the true energy use of lighting in buildings requires an understanding of not only what types of lighting systems are used, but how those systems are operated throughout the year. Advancements in lighting control technology and the green building movement have combined to create a design atmosphere that relies on lighting controls, both manual and automated, to reduce energy costs. The effectiveness, though, of these controls in saving energy must be quantified, both for new construction projects and existing buildings, in order to understand the potential cost-effectiveness of such systems.

Manual Lighting Controls

Understanding and quantifying the use of manual controls is key to being able to understand and quantify the use of lighting energy. Manual controls have served as the fundamental control type since the advent of electric lighting. Moreover, manual controls can serve as the "ideal" control, if the person using the controls behaves "ideally". That is, if the occupant in the spaces is well attuned to their visual needs and the availability of daylight in their space, they can serve as the ideal controller. Automated controls simply aim to mimic this ideal behavior by anticipating the user needs.

Understanding and providing models of manual control of lighting in buildings first became of interest in the 1970s. Hunt (1979) undertook the first published research that used time-lapse photography to gather occupancy and lighting related data for various space types, including multi-occupant offices, classrooms, and combined teaching spaces. Images were recorded in 8-minute increments over the course of one half of a solar year, and were used to assess the status of the lighting and blinds, accounting for partial-load conditions (e.g. alternate

row switching). Total and diffuse horizontal solar illuminance data were also recorded at a local weather station.

Hunt grouped the various spaces into two general occupancy types, intermittent and continuous. It was found that the intermittently-occupied spaces exhibited switching events scattered throughout the day and tied to the times of occupancy. In general, the peak times for 'switch-on' events were found to be at the beginning of the day, at the beginning of each occupied period and at the beginning of cleaning times. Conversely, the peak times for 'switch-off' events were found to be at the end of occupied periods, at the end of the day, and at the end of cleaning times. Lighting energy use was also found to have a significant relationship to the availability of daylight, with decreasing lighting energy consumption resulting from increasing daylight illuminances. The time-lapse photography also showed that the lights were left on when the room was unoccupied only 3% of the time.

The continuously-occupied multi-person offices were found to have very different switching patterns. It was found that, because of generally-continuous in and out activity, the spaces were rarely completely unoccupied, and thus the lighting was generally switched on at the beginning of the workday and switched off at the end. Mid-day switching events were rare, and likely due to reduced daylight illuminance levels. Hunt concluded that, for these types of multi-occupant spaces, the previous state of the lighting generally had the largest effect on the current state; in other words, if the lighting was on, it would be left on, if off, it would be left off. It was concluded that this small probability of intermediate 'switch-on' events was likely due to a reluctance to change the environment in a shared environment out of concern for other occupants, adaptation to reduced illuminance levels, or infrequent occurrences of low daylight

illuminance levels. The small probability of intermediate 'switch-off' events was likely due to many of the same factors, especially visual adaptation.

From this data, Hunt was able to develop a single curve relating the workplace illuminance to the probability of a 'switch-on' event at arrival, as shown in Figure 1.
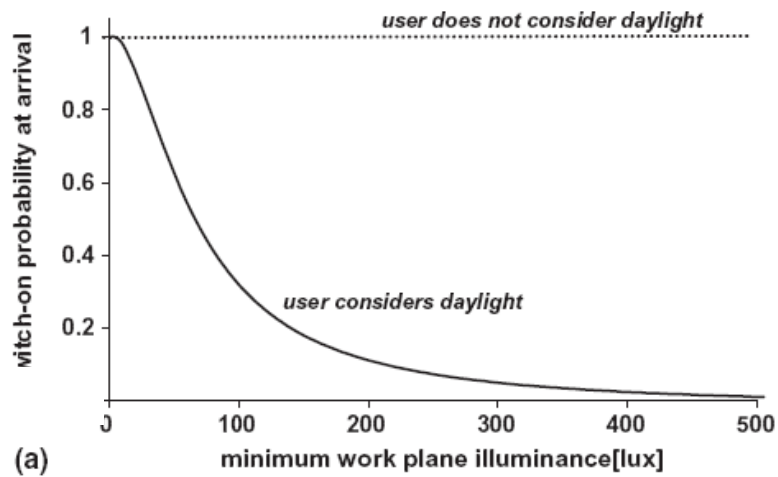
Figure 1: Switch-on Probability at Arrival, from Hunt 1979 as reproduced in Reinhart 2003

In *Monitoring manual control of electric lighting and blinds* (Reinhart & Voss, 2003), results were presented from a data collection effort focused on ten daylighted offices in Germany. As shown in Figure 2, the data showed a very strong correlation with the Hunt 1979 curve, despite decades and continents of separation. Additionally, the results of a 12-month data collection study based on office spaces in Austria (Mahdavi, Mohammadi, Kabir, & Lambeva, 2008) found a very similar relationship between 'switch-on' probability and workplane illuminance as shown in Figure 1 and Figure 2.
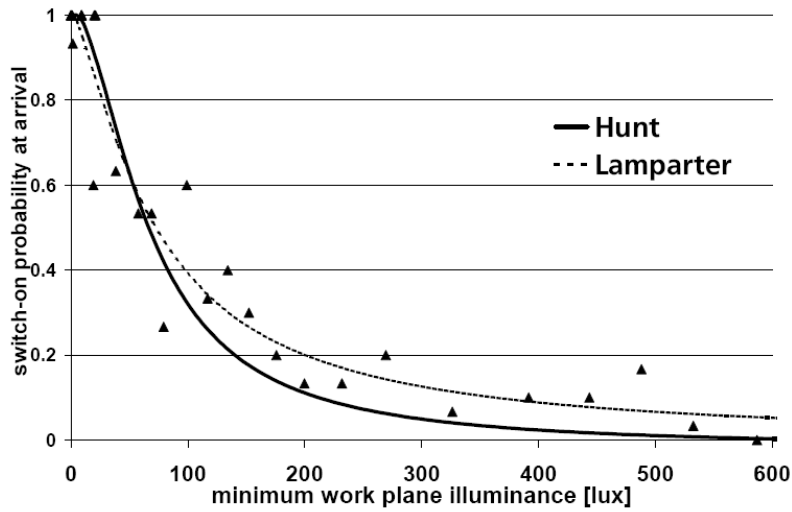
Figure 2: Switch-on Probability of Arrival, Comparing Hunt's 1979 curve to the Results in (Reinhart & Voss, 2003).

Reinhart & Voss also presented additional conclusions regarding the probability of an intermediate 'switch-on' event as a function of minimum workplane illuminance. As shown in Figure 3, the probability of an intermediate 'switch-on' event was found to remain essentially static below 20 fc, with a probability of 2%. Similarly, above approximately 30 fc, the probability is reduced to less than one half of one percent.
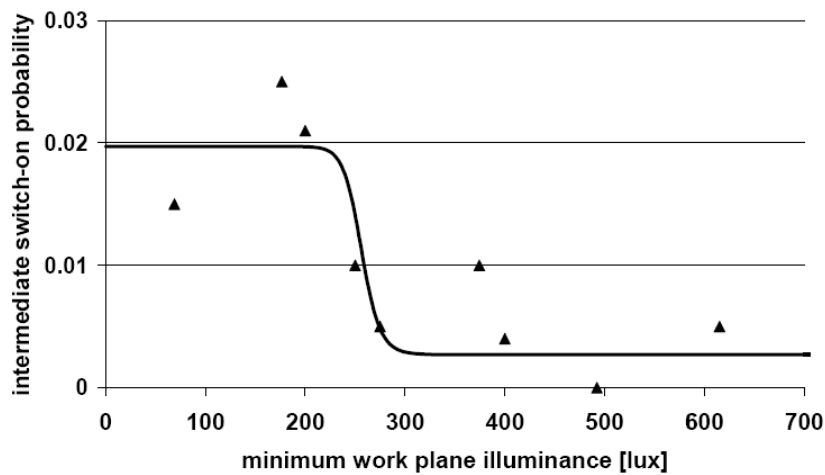
Figure 3: Intermediate switch-on probability as a function of the minimum workplane illuminance, from (Reinhart & Voss, 2003)

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Additionally, Reinhart & Voss investigated the probability of 'switch-off' events as a function of expected duration of absence, and compared their results qualitatively to that found in previous research (Pigg, Eilers, & Reed, 1996), as shown in Figure 4. As shown, the probability of a 'switch-off' event at departure increases with the increasing duration of the expected absence for all types of control systems. Most strikingly, the probability of a 'switch-off' event with only manual controls approaches unity when the expected duration reaches four hours, where the probability based on the dimmed system never exceeds 75%. The authors concluded that, based on anecdotal evidence, it was likely that the occupants did not notice that the dimmed system was on at departure.
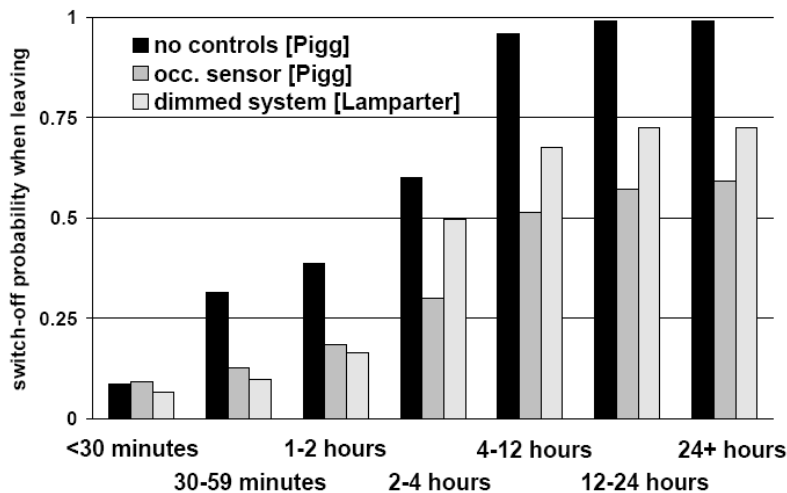
Figure 4: Switch-off probabilities as a function of anticipated absence, from (Reinhart & Voss, 2003).

Mahdavi et al. (2008) also investigated the probability of a 'switch-off' event as a function of anticipated duration for three manually-controlled office lighting systems, and found a similar relationship, with the probability of an event increasing with increasing duration of anticipated absence.

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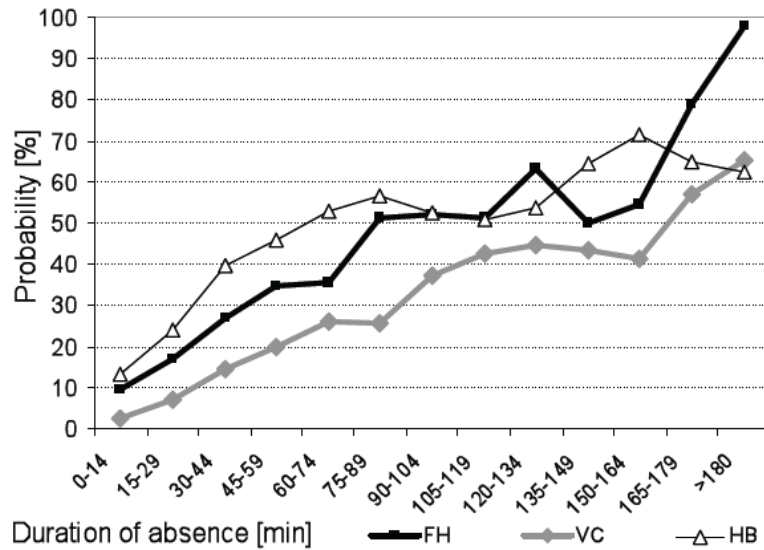
Figure 5: Probability of a 'switch-off' event as a function of expected duration of absence, from (Mahdavi, Mohammadi, Kabir, & Lambeva, 2008)

Mahdavi et al. also investigated the occurrence of intermediate 'switch-off' events, and found that the probability increases with increasing task illuminance in the three buildings studied, as shown in Figure 6. The authors conclude that this indicates a general relationship, though no strong correlation was found during this effort.
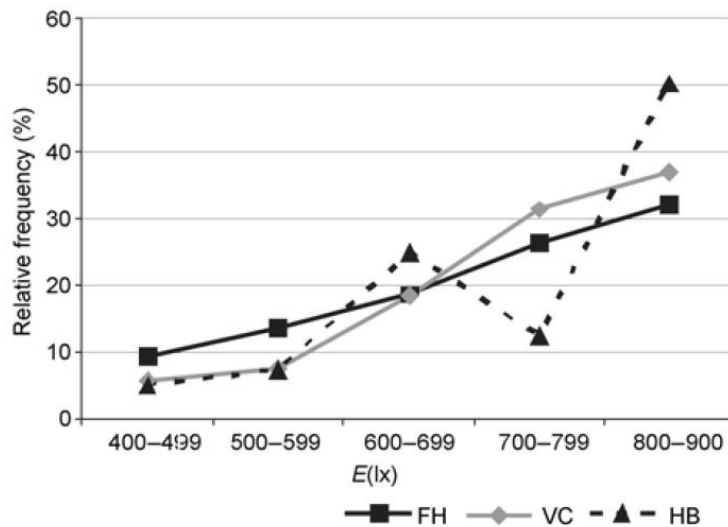
Figure 6: Relative frequency of an intermediate 'switch-off' event as a function of workplane illuminance, from (Mahdavi, Mohammadi, Kabir, & Lambeva, 2008)

Finally, Lindelof & Nicolas (2006) investigated intermediate switching activities in offices in the LESO building in Lausanne, Switzerland. This building is highly automated and has integrated sensors, control systems and data collection systems that allow for extensive testing of building control strategies, including passive design and advanced control algorithms. The goal of that research effort was to determine if a relationship exists between horizontal workplane illuminance and intermediate switching events. In order to evaluate this particular aspect of manual control, the authors gathered time-based switching event data in reference to occupant time of arrival, and looked solely at the actions that were taken at least five minutes after arrival and at least one minute prior to departure based on a statistical analysis of the occurrence of switching events with respect to arrival times. The concluded general relationships between illuminance and intermediate events, as shown in Figure 7 and Figure 8, represent the aggregate data for fourteen offices with continuous monitoring for over three years.
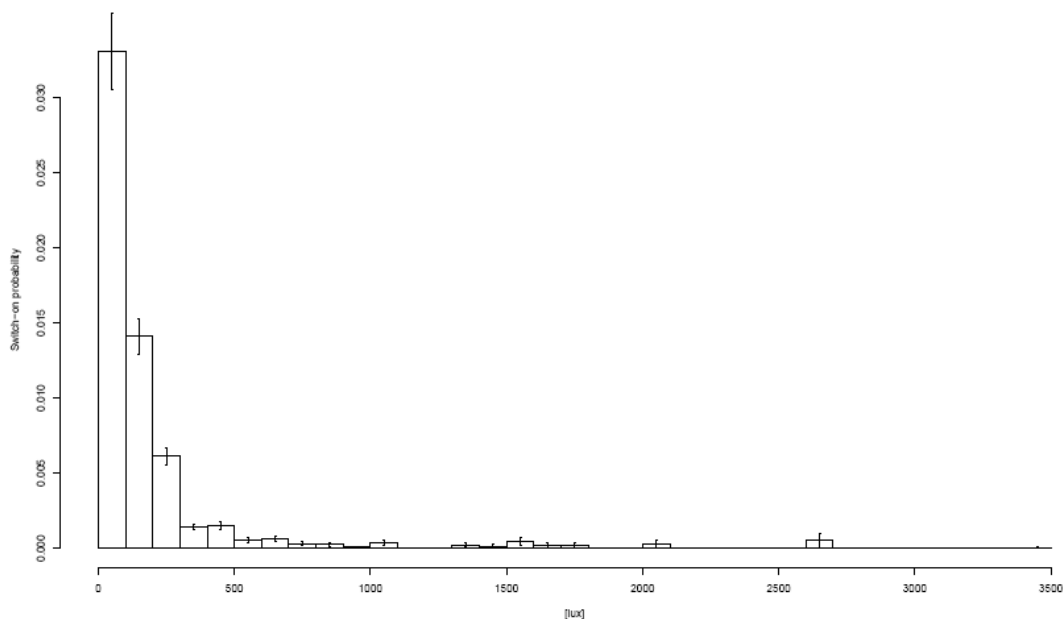
Figure 7: Intermediate 'switch-on' probabilities from (Lindelof & Nicolas, A field investigation of the intermediate light switching by users, 2006)

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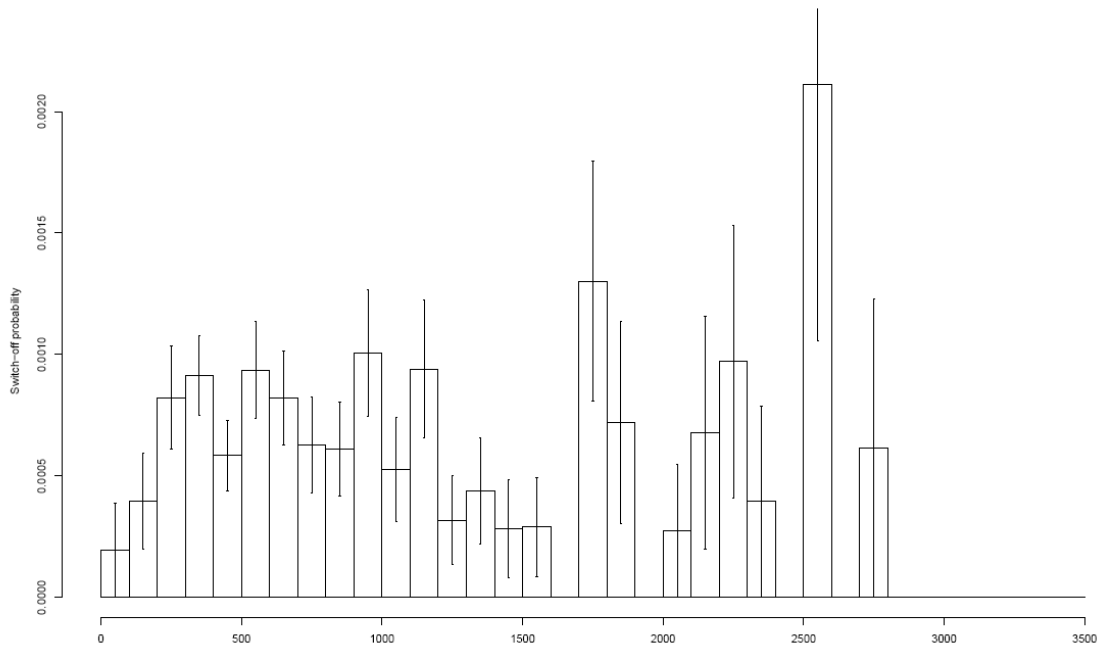
Figure 8: Intermediate 'switch-off' probabilities from (Lindelof & Nicolas, A field investigation of the intermediate light switching by users, 2006)

In general, the results of these empirically-based studies have shown significant and repeatable relationships, based on large empirical data sets, between interior conditions and actions on manual lighting control systems with regard to 'switch-on' events and intermediate switching events. Significant relationships have also been found for 'switch-off' events, though the results have not been replicated. These relationships have been incorporated in many investigations, and the use of these probabilistic functions will be further discussed in their incorporation into the Lightswitch-2002 model (Reinhart C. F., 2004).

Manual Blind Controls

The operation of manual blinds has also been investigated in previous studies. Operation of shading devices is not only of interest with regards to interior daylighting, but the impacts on cooling loads, and to a lesser extent on heating loads, can be significant.

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As summarized in (Reinhart C. F., 2004), previous research has led to an understanding of the criteria for closing blinds, though repeatable conclusions regarding blind opening actions have not been found. For example, as shown in Figure 9, the results from two empirically-based studies demonstration revealed different relationships between solar penetration depth and shade deployment. Inoue et al. (1988) found a linear relationship, while Reinhart & Voss found a more logarithmic relationship for a particular building in Germany (called Lamparter here).
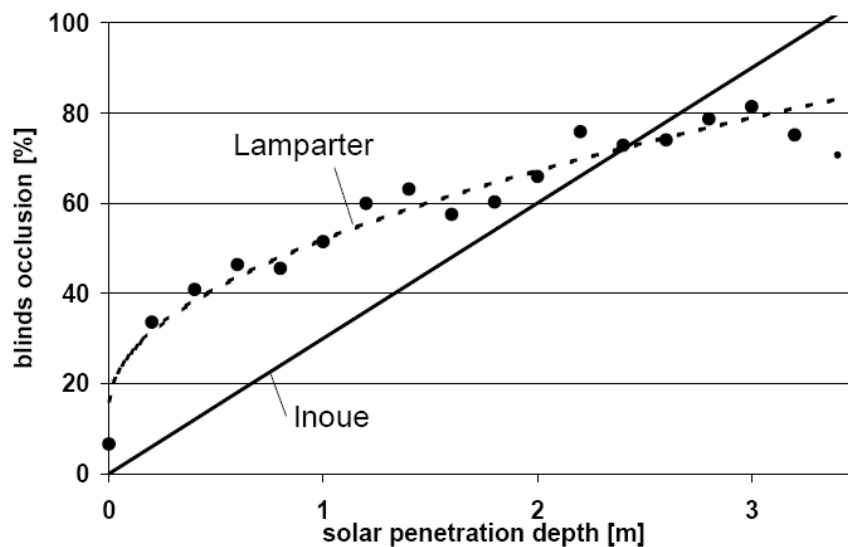
Figure 9: Shade deployment as a function of direct sun penetration depth, as reported in (Reinhart & Voss, 2003)

Figure 10 shows the results presented by Mahdavi et al. (2008) regarding shade deployment for three different orientations, where "VN" indicates a north facing window, "VS" indicates a south facing window and "FH" indicates an east facing window. Their results indicate that shade deployment was independent of external vertical irradiance, and thus illuminance, for north and south facing windows, with the shades on north facing windows being rarely used and shades on the south facing windows being commonly used. For the east facing windows, a relationship that approaches linear was found.
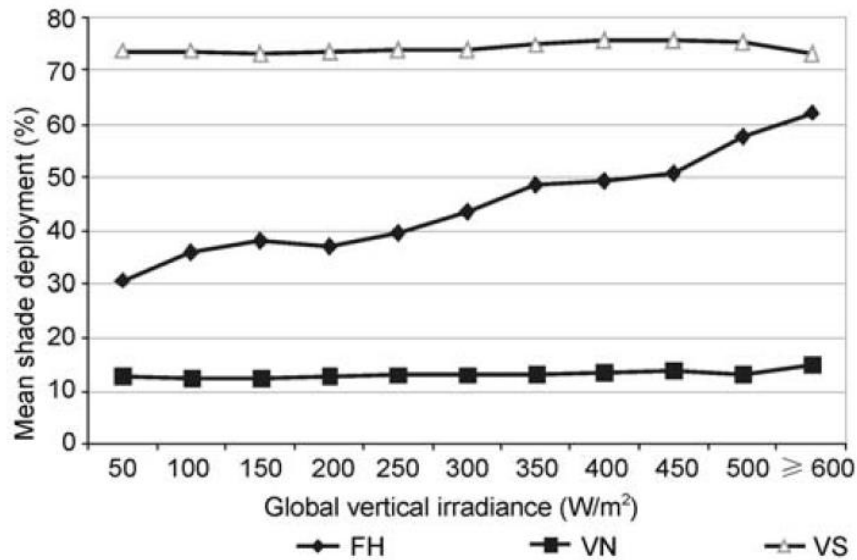
Figure 10: Shade deployment as a function of vertical irradiance from (Mahdavi, Mohammadi, Kabir, & Lambeva, 2008), where the space 'FH' faces east, 'VN' faces north and 'VS' faces south

Most recently, Haldi and Robinson (2010) provided an algorithm for simulating occupant interaction with manual blinds that was a result of a 6-year data collection effort at the LESO-EB building. During the data collection period, the authors gathered information regarding the position of the lower (view) window shading and the upper (daylighting) window shading in terms of an open or closed position. Simultaneously, they gathered information regarding the occupancy state via occupancy sensors, interior workplane illuminance, and exterior daylighting data including global horizontal illuminance and direct beam illuminance. Based on the correlations found, the authors developed a procedure for simulating the action of occupants on a shading device, as shown in Figure 11. As shown, the main influencing factor that informs the likelihood of a blind adjustment action at all times is the average workplane illuminance. At arrival, the blind status from the previous time was found to influence the likelihood of adjustment, noting that the occupant likely found the previous blind state inadequate given the

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current daylighting conditions. When examining intermediate actions, the outdoor global

horizontal illuminance was found to impact the likelihood of adjustment, since the occupant was

generally found to adjust based on glare conditions. Based on these interactions, the authors

presented a series of functions that describe the likelihood of blind action (raising or lowering),

given the occupancy status (or change), as well as the identified influencing factors. This blind

operation model again is based on the private office paradigm. The authors noted that in

multiple-occupant offices, the probability of adjustment was dampened.

In general, it was noted that occupants are more likely to adjust their blinds upon arrival

than during periods of persistent presence, and confirmed previous assumptions that occupants

were unlikely to adjust their blinds upon departure. Additionally, it was noted that intermediate

actions on the blinds were very rare, similar to the patterns observed regarding intermediate

actions on the electric lighting systems. Another interesting note was the observed pattern that

raising actions are far more likely to occur than lowering actions, due mostly to the fact that the

majority of the lowering actions resulted in a fully lowered position, thus requiring fewer

adjustments. Raising actions were observed to occur in smaller increments, not often resulting in

a full raising action and thus occurring more often. Finally, it was generally observed that the

blinds used to control the upper windows, which serve for daylighting purposes, were more

likely be changed in response to changing conditions or occupancy status changes, where the

status of the blinds covering the view windows were less likely to change due mostly to the

desire to preserve the view. This phenomenon may also in part be due to the orientation of the

observed offices as facing due South in the Northern hemisphere, which likely resulted in a

situation where little direct beam illuminance on the work surfaces was due to beam illuminance

through the view windows and more likely due to beam illuminance through the upper windows.
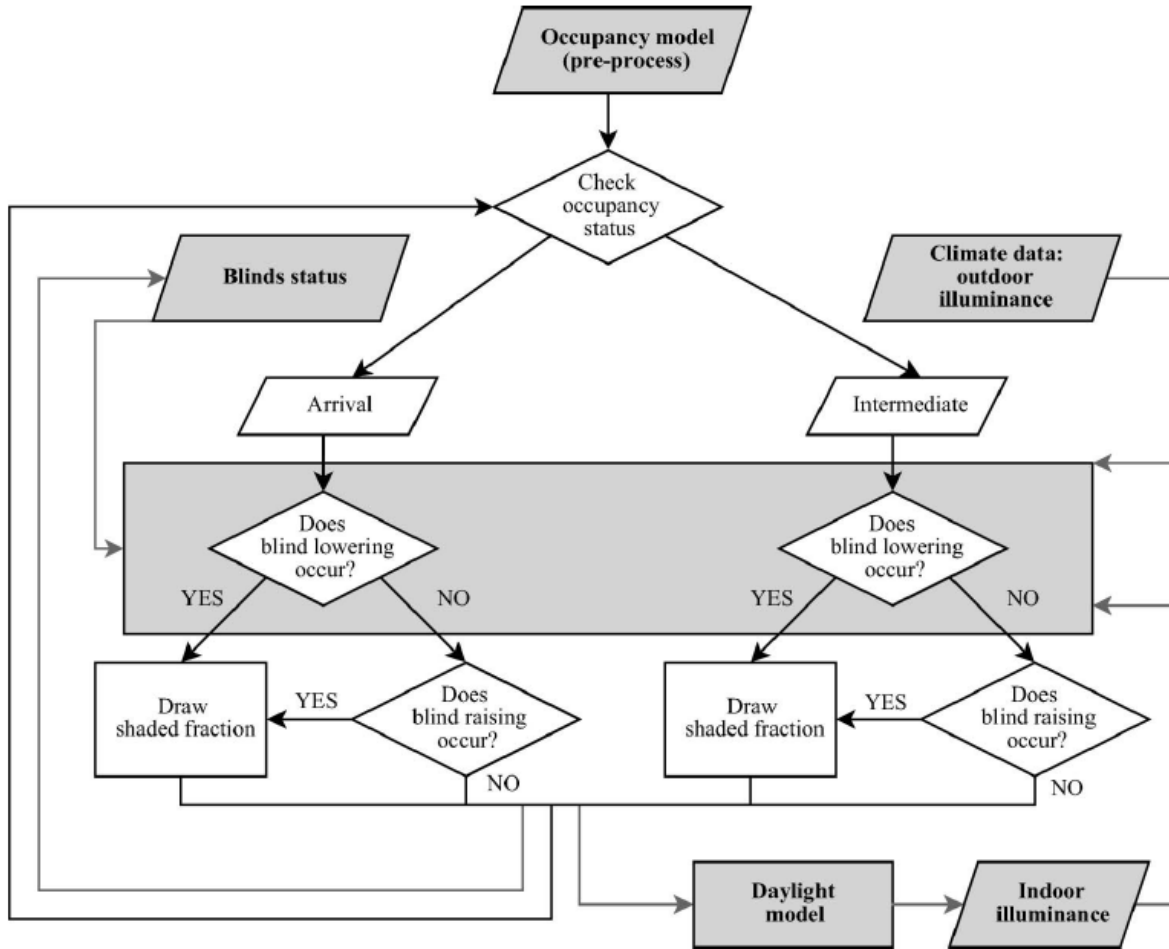
Figure 11: Manual blind action modeling algorithm. (Haldi & Robinson, Adaptive actions on shading devices in response to local visual stimuli, 2010)

Daylighting

When quantifying the use of electric lighting, it is imperative to consider the impact of daylighting. This is true both when manual controls exist and when automated controls have been installed. In the case of manual controls, it is important to recognize that the switching behavior of occupants may or may not be directly dependent on their available daylight. This includes illuminance on the workplane, which can directly offset the need for supplemental

electric lighting, but also the environmental luminance, such as ceiling brightness, overall

contrast, and the impact of interior finishing.

When considering automated controls, it is important to understand the integration of

daylight into dimming and switching schemes designed to maximize energy savings by

minimizing electric lighting use when sufficient daylight is present. Automated systems rely on

either closed-loop photosensors, which typically will measure the resultant interior illuminance

on the ceiling using a photosensor, or an open-loop system which may rely on the data gathered

from a pyrometer or photosensor mounted on the exterior of the building. Closed-loop

photosensors may be subject to user overrides due to their accessible location; additionally,

closed-loop photosensors may face issues of changing interior reflectances which increase the

brightness on the photosensor itself without actually increasing the illuminance on the

workplane, such as when a large set of white drawings are unfurled on an architect's dark desk

directly below the sensor.

Daylighting Metrics

Various metrics for quantifying daylighting have been proposed (Refer to Mardaljevic,

Heschong, & Lee, 2009 for a comprehensive review).

Daylight Factor is a very common metric, first proposed in the early 1900s, and is used as

a reference in many green building rating systems (Mardaljevic, Heschong, & Lee, 2009).

Daylight Factor (DF) is considered a proxy for actual daylight availability, and is defined as the

ratio of interior illuminance to exterior (unobstructed) horizontal illuminance under a

rotationnally-symmetric overcast sky typically evaluated on a point-by-point basis and averaged

for a space. DF does not consider direct sun light, and is expressed as a percentage of

availability that does not provide information on absolute interior illuminance levels with regard

to desired task illumiances. Additionally, DF does not account for seasonal variations, the impact of orientation, or differeces due to physical location. DF has been shown to be a poor predictor of actual interior daylight conditions, even under overcast skies (Teregenza, 1980). Furthermore, DF has been shown to be a poor predictor of dynamic lighting conditions (Littlefair, 1992).

Daylight Autonomy (DA) is another popular metric, though it is not yet incorporated into codes and standards. The calculation of point-by-point DA values involves determining the fraction of the occupied year, expressed as a percentage, where the workplane illuminance due to daylight (direct solar and diffuse sky light) meets or exceeds the design illuminance. Point-by-point values are then typically averaged for a room to determine a rating. While DA provides an advancement through its direct connection to the design illuminance levels, it likely does not accurately account for the impact of exceedingly high interior illuminances.

Useful Daylight Illuminance (Nabil & Mardaljevic, 2006) provides an additional refinement. The calculation of point-by-point UDI involves evaluating the illuminance from direct and diffuse daylight, including interreflections, with respect to the design illuminance but also based on empirical data regarding blind-closing actions. It was found that below 100 lx (~10 fc), daylighting was insufficient to be autonomous to the point where occupants activated their electric lighting. Conversely, above 2,000 lx (~200 fc), the daylighting was so high that blinds were closed and electric lighting was activated. The range of UDI, therefore, is considered the percentage of the annual occupied year where the interior daylight illuminance falls within the range of 100 lx to 2,000 lx.

When incorporated into electric lighting and energy analysis simulations, the UDI range can further be split based on the design interior workplane illuminance. For example, if the

design workplane illuminance for an office was 350 lx, the daylighting would be considered 'Supplementary' from 100 lx to 350 lx and would be considered 'Autonomous' from 350 lx to 2,000 lx. This allows for an understanding and quantification of essentially the effectiveness of the interior daylighting.

Lighting Calculation Methods

Two main methods for calculating indoor lighting are generally used throughout the lighting industry: radiosity and ray-tracing.

The radiosity method essentially examines the steady-state energy transfer of lighting in a space. The method involves first determining the initial exitance of interior surfaces, which have been descritized into small patches typically limited by the space geometry, based on the intensity distribution of luminaires. Interreflections are then considered based on the relative position of each descritized patch and their initial exitance. The steady-state illuminance on each patch is then determined accounting for both the initial illuminance and the illuminance due to interreflections. When considering daylighting, most radiosity-based software create intensity distributions which are physically located at the window and account for direct solar and diffuse sky luminance, and which are subsequently treated as typical luminaires.

Ray-tracing solutions are based on the concept of actually tracing the "rays" of light, and can be executed in either forward or backward configurations. In forward ray-tracing, rays are cast from luminaires, the sun, or the sky, with the relative quantity based on the intensity distribution. The rays are then followed as the intersect surfaces and are bounced off or transmitted through those surfaces. Typical software allows the user to limit the number of bounces considered in the calculation. Backward raytracing is typically used for the generation

of renderings, and involves tracing possible rays back from each surface, through a set number of bounces, to the original source.

In general, radiosity and ray-tracing are both acceptable methods for calculating interior lighting condition based on a set configuration. Radiosity solutions typically require lower computing power than ray-tracing solutions, but typically result in much more "patchy" appearances in renderings. Ray-tracing solutions are typically more accurate at capturing the shapes and patterns of light and shadow distribution, and are able to incorporate non-Lambertian surfaces, but require significantly more computing power. However, both methods are considered valid methods for calculating and rendering lighting.

Daylighting Calculation Models

EnergyPlus, an advanced energy modeling simulation tool, currently uses a modified Daylight Factor to determine the impact on lighting energy and cooling. EnergyPlus uses the DOE-2 detailed daylighting calculation module, which employs the 'split-flux' method of calculation. The 'split-flux' method essentially splits the direct solar flux from the diffuse sky and ground-reflected flux. Based on a typical radiosity solution scheme, the illuminance at points due to direct solar and electric light is first calculated, and then the diffuse contributions due to interior interrefleciton and diffuse sky and ground-reflected light is determined. The Daylight Factor at each point is then calculated typically as the ratio of interior illuminance to available exterior illuminance, though the direct solar is considered in both values.

Work is currently being done by other research teams to integrate the Radiance daylighting calculation engine to run as a co-simulation with ESP-r and EnergyPlus to include the impact of more detailed lighting calculations on lighting energy through the use of automated controls (Janak, 1997). Radiance is a CIE-validated open-source calculation procedure that

provides significantly more detail to the lighting simulation than the split-flux method had has

been validated per CIE 171:2006 (International Commission on Illumination, 2006) unlike the

split-flux method. Validation per CIE 171:2006 ensures sufficient accuracy of the calculation for

lighting purposes, and is generally undertaken only for software that is intended for detailed

lighting calculations.

Daylighting Sky Type Definitions

The various methods of modeling daylighting typically rely on a combination of direct

(sun) illuminance and indirect (sky) illuminance to contribute to interior light levels. While it is

fairly simple and straightforward to quantify the exact location of the sun and the brightness of it,

the sky definition is much more variable and therefore much more challenging.

The CIE has mathematically identified a set of fifteen "standard skies" that are

recommended for use in daylighting calculations (International Commission on Illumination,

2003). Each of these skies is assigned a "Gradation Group," which is a ranking to indicate the

luminance gradation between the horizon and zenith. Each sky is also assigned a "Indicatrix

Group," which groups sky models based on the amount of scattering, allowing the position of the

solar disk to impact sky luminance distributions.

A clear sky definition is the most standard, and industry-standard software relies on the

Kittler clear sky model (Lighting Analysts), which is identified by the CIE as Sky Type 12. This

sky definition is in Gradation Group V (out of VI), indicating that there is large gradation from

horizon (highest luminance) to zenith (lowest luminance). Sky Type 12 is also in Indicatrix

Group 4 (of 6), indicating that the sky patch luminances are more influenced than others by the

position of the solar disc, leading to high circumsolar brightness and eliminating rotational

symmetry. To note, the CIE recognizes a second clear sky model, Sky Type 13, which is

identified as appropriate for a location with a polluted atmosphere. So, while Sky Type 13 still falls into Gradation Group 5, it is raised to Indicatrix Group 5, since the increased pollution increases sky turbidity and therefore increases the influence of the position of the solar disc on sky patch luminances.

The CIE recognizes four overcast sky models. The default sky model for most industry-standard software is Sky Type 1, which is the CIE default model for overcast skies and is based on the Moon and Spencer model (Lighting Analysts). This model falls into Gradation Group 1, indicating minimal gradation difference between the horizon and zenith, and Indicatrix Group 1, indicating little variation due to scattering. This particular sky type also concentrates the luminance gradation toward zenith, and is azimuthally uniform. The three other overcast sky models introduce increasing levels of gradation and increasing influence of scattering, and also incorporate asymmetrical circumsolar brightening.

Partly cloudy skies are much more difficult to define, and there are currently five partly cloudy sky models recognized by the CIE. These models vary based on their treatment of circumsolar brightness, and the gradation of the sky brightness. However, the models assume, excluding the influence of the Indactrix Group, a rotationally symmetric sky, which assumes equal cloud densities and distributions across the sky. In essence, the partly cloudy sky models simulate a uniform partial increase in sky brightness, as if applying the impact of broken clouds to the complete sky dome to reduce the overall luminance. The sky models do not expressly include the recommended brightness and position of cloud cover, but instead examine in an aggregate sense the impact of partly cloudy skies on the overall sky luminance distribution.

The IES handbook (DiLaura, Houser, Mistrick, & Steffy, 2011) additionally recognizes the challenges associated with modeling the various sky types. In general, they state that the sky

models should not be compared to instantaneous sky conditions. For example, the mathematical model of a partly cloudy sky that has been evaluated over time should not be compared to the instantaneous distribution of clouds and the illuminance thus created. Therefore, it is important when considering the daylighting aspect of energy modeling to understand that the instantaneous readings will not necessarily align with modeling capabilities. In the modeling of other building energy systems like HVAC, the instantaneous exterior temperature and wind speed, for example, can be used directly in predictions of energy use under those conditions. With daylighting, however, the instantaneous sky conditions may or may not match the mathematically-defined sky type at any particular point, though in aggregate the experienced illuminance due to sky and sun brightness may align with that predicted by the model. It is therefore very critical to make sure that any lighting energy simulation that involves daylighting simulation be examined not on an instantaneous basis, but on an aggregate basis.

Lighting Energy Models

When modeling lighting energy, there are two general methods. Deterministic scheduling, which is the reliance on static hourly or sub-hourly schedules, is the most common type of energy modeling tool, and is currently incorporated into a wide variety of energy analysis protocols. More advanced stochastic models, which include the variation in user behavior, are currently emerging, and incorporate an intuitive variation in behavior that is absent in the deterministic schedules.

Deterministic Scheduling

The most basic method for simulation lighting energy use is through the inclusion of deterministic lighting energy use schedules. Deterministic use schedules typically provide hourly relative use intensity as a percentage of the total installed power. Typically, these

schedules do not account for individual deviations. They are designed, in general, for use in estimating hourly energy use and as such do not generally lead to appropriate methods for estimating peak demand.   Many such schedules have been published and are used throughout various research projects and simulation tools.

The California Energy Commission (CEC) oversees the creation and execution of the California Non-Residential Energy Code, known as Title 24 Part 6. As a part of this code, the CEC allows for two different methods of compliance. The first, and simplest, is to demonstrate compliance through addressing individual components or systems, such as fan efficiency or installed lighting power density. The second method, which allows for the assessment of atypical buildings, is known as the Alternative Compliance Method (ACM). In the manual for this method (California Energy Commission, 2005), the CEC provides guidelines for the simulation of annual building energy use based on the DOE-2.1e calculation engine created and managed by Lawrence Berkeley National Labs (LBNL). A part of the ACM manual includes a deterministic schedule of relative energy use intensity per hour for non-residential non-mall buildings for typical weekdays, Saturdays and Sundays. The ACM does not allow alternative methods for simulating energy use intensity, instead relying simply on this deterministic schedule applied to the building lighting power. While this does allow for hour-by-hour demand and energy use to be simulated, there is no variation on a day by day basis, which intuitively seems like a gross underestimation of the inherent variability of personal lighting energy use.

The National Renewable Energy Laboratory (NREL) has published a manual documenting the energy simulation procedure required to qualify for federal energy efficiency tax incentives (Deru, 2007), a national program. In that document, the authors give guidance and requirements for simulation parameters required to demonstrate improved energy efficiency.

Within that document, various deterministic load schedules are provided for use as inputs into advanced energy modeling programs. For lighting, the authors refer to and include the same lighting intensity use for non-residential non-mall buildings as included in the California ACM Approval Manual. Similarly, no guidance is provided for including any variability in energy use intensity beyond this deterministic schedule.

Figure 12 illustrates the deterministic lighting energy use intensity included in the California ACM and referred to in the NREL guidelines. As shown, the peak maximum use never exceeds 85% and the minimum use never falls below 5%. Saturdays are assumed to have larger uses than Sundays, though both are significantly lower than the typical weekday use.
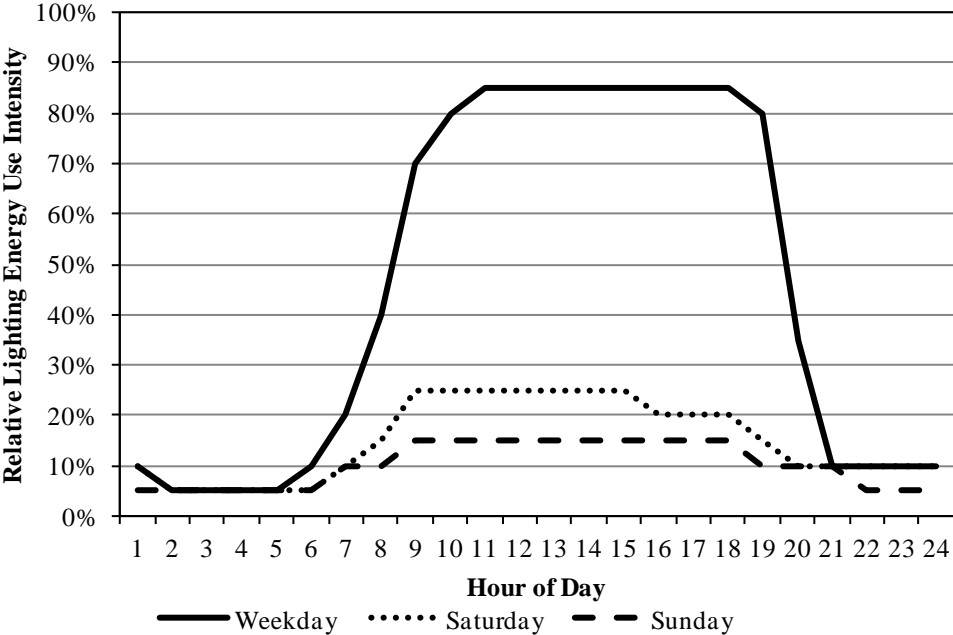
Figure 12: Lighting energy use intensity from the California ACM.

EnergyPlus is a simulation building energy tool that created and managed by the Building Technologies Program of the US Department of Energy Energy Efficiency & Renewable Energy office. EnergyPlus is a tool used to simulate building energy use, including various energy expenditures, such as heating, cooling, fans, pumps, lighting, plug loads, and other miscellaneous

25

loads. EnergyPlus is a tool that takes inputs and creates outputs in the form of text files. The

simulation protocol includes default schedules for various components. For example, a schedule

of occupancy is used to assess the impact of thermal and latent heat gains from the number of

occupants. Similarly, estimates of energy use intensity for lighting and plug loads are provided.

Figure 13 includes the hourly relative lighting energy use intensity that is provided in the

EnergyPlus documentation as a sample for office buildings (US Department of Energy, 2011).

As shown, the peak weekday lighting energy use never exceeds 90%, and the energy use never

falls below 5%. Saturdays assume moderate daytime occupancy leading to moderate lighting

energy use. Sundays sit entirely at 5% lighting energy use throughout the day, essentially

illustrating the assumption that the building is unoccupied on Sundays and thus the only

consumed lighting energy is the standby power seen during other unoccupied times.
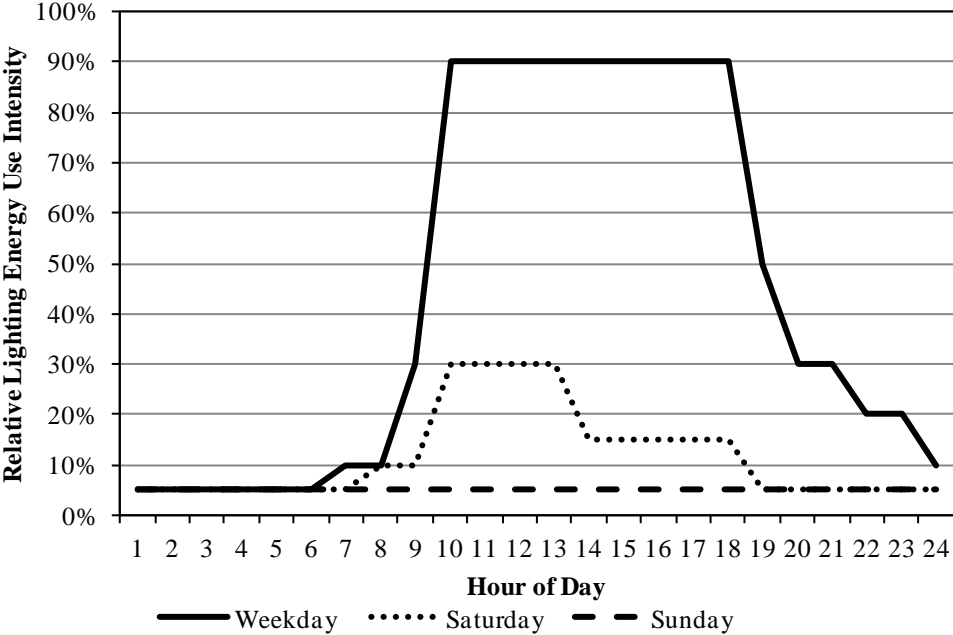
Figure 13: Lighting energy use intensity from the EnergyPlus defaults for Office Lighting.

For simple estimation used to assess cost-effectiveness of controls during the design

phased, designers and engineers often rely on knowledge of the specific building to create

project-specific deterministic schedules. For example, should the office hours be known, it may be assumed by the engineer that the lighting will be fully activated throughout the business hours, and completely or nearly-completely extinguished after hours. While this type of schedule assumption is not based on empirical data, the reliance on actual known parameters of the building can potentially lead to more accurate predictions of peak demand and overall energy use. However, these assumptions require a priori knowledge of the operation of the building, which is oftentimes unknown especially when considering speculative construction projects.

In general, deterministic lighting schedules provide hourly relative lighting energy use intensity and distinguish between weekdays and weekend days for various space types. In general, these schedules are meant to capture only energy use over that specific hour, and do not state any clear assumptions about operation within that hour. For example, if the energy use intensity over a single hour is 90%, that could translate to all of the lighting activated for 90% of that hour, or 90% of the lighting activated for the full hour. As such, directly estimating peak demand from these types of deterministic schedules requires the understanding that the type of data being presented is interpretable in various manners.

Lightswitch-2002 Model

The most commonly employed model for the manual operation of blinds and manual controls as it relates to lighting energy use was originally developed as the Lightswitch model (Newsham, Mahdavi, & Beausoleil-Morrison, 1995). The Lightswich model provides a framework for modeling the impact of occupant actions on building systems in 5-minute increments for incorporation into DOE2-based simulations.

Fundamentally, the Lightswitch model relies on stochastic occupancy modeling based on empirical data gathered in a group of private offices. Arrival times were recorded based on

computer log-on information, temporary absences were recorded by walk-throughs, and

departures were chosen based on the typical times of the end of work. The data analysis

involved determining action functions, which describe the probability of various actions,

including arrival, temporary absence and departure, as a function of the time of day for private

offices.

The Lightswitch model was then applied to a lighting energy simulation that incorporated

true occupancy sensors (Auto-On/Off), as opposed to vacancy sensors (Manual-On/Auto-Off),

with a 10-minute delay time to evaluate the energy savings from the sensors. At each 5-minute

increment, it was determined if an occupancy event (arrival or departure) had occurred, and how

long the space had been in the current occupancy 'state.' This allowed the examination of the

impact of the dynamic occupancy scheduling on occupancy-based lighting controls to be

compared to the results using a standard static hourly schedule.

The Lightswitch-2002 model (Reinhart C. F., 2004) so far has represented the most

advanced modeling algorithm for lighting energy in private offices. This evolution of the

original Lightswitch model continued on the foundation of stochastic occupancy modeling.

However, instead of being limited to idealistic automated controls, the Lightswitch-2002 model

expands to include a method for evaluating the impact of manual controls over lighting and

blinds.

The Lightswitch-2002 model requires inputs including the workplane daylight

illuminance in 5-minute increments, and measured or simulated occupancy profiles in 5-minute

increments. At each time step, the algorithm processes the occupancy and blind data according

to deterministic rules for automatic controls and probabilistic functions for manual controls.

Within the process, the state of the blinds is first set, and then the associated manual or automatic

lighting control is set. This allows for the lighting energy intensity in 5-minute increments to be established.

The process of setting blinds within the Lightswitch-2002 model was established as either *Automated* or *Manual*. Both blind conditions assumed venetian blinds that are lowered fully when the direct solar irradiance exceeds 50 W/m^2. The slat angle, restricted to three different angles, is set to avoid any direct solar. The automated blind control was assumed to dynamically adjust throughout the day in response to solar availability. The manual blind control was assumed to be re-opened only once per day, at initial arrival, and left closed once closed.

For manual lighting control, two scenarios were incorporated to evaluate manual switch-on behavior upon arrival, a uniform probability of 100% for a user that does not consider daylight, and a variable curve based on the work of Hunt (1979) for a user that does consider daylight, as shown in Figure 1. These types of users can be considered *Active* and *Passive*. The intermediate switch-on probability function used in the model, for *Active* users, was drawn from the work of Reinhart & Voss (2003), as shown in Figure 3. Finally, the switch-off probability at departure was based on the work of Pigg et al. (1996) and Reinhart & Voss (2003), as shown in Figure 5, and was applied to both *Active* and *Passive* users.

While the Lightswitch-2002 model represents a large advancement in the prediction of lighting energy usage, there are limitations to the model which make its extension challenging. First, the basic model relies on switching probability functions derived for private spaces where occupants spend significant time. This limits the applicability of the model to private spaces, such as private offices, where occupants feel 'ownership' over the space. Second, the granularity for blind control is low, assuming only fully-open and fully-closed positions and with closing decisions based not on interior illuminance or brightness, but on horizontal workplane irradiance.

The Lightswitch and subsequent Lightswitch-2002 models have been incorporated into other research and modeling efforts. Bourgeois et al. (2004) incorporated the Lightswitch occupancy and control models into their framework for integrating high-resolution occupancy simulations into the larger framework of energy modeling. Bourgeois et al. (2005) also incorporated the Lightswitch-2002 model into their study comparing the impact of incorporating manual control to reference cases where the occupancy and lighting use is static throughout the day.

Occupancy-Based Controls Model

Previous work examined the potential energy savings from occupancy-based lighting controls (Degelman, 2000) and (Degelman, 1999). The author collected occupancy data streams from various space types in terms of occupancy status (occupied/not occupied) over time. Those data streams were combined to determine the probability at each minute that an occupant would arrive, which was then used to drive a Monte-Carlo simulation. Simple time-based analysis was performed based on various time-out periods to find the overall 'ON' time for the system. This work is significant in that it provides a framework for the incorporation of time-related binary occupancy status data into a lighting energy savings calculation method based on automated controls. The calculations assume a sensor that functions with Auto-On capabilities, so therefore the lighting is activated at every arrival independent of pre-arrival luminous conditions.

Occupancy Models

The need to understand the movement of building users within a space has become a more pressing issue as advanced buildings trend toward providing higher degrees of user control and operability. Historically, building energy simulations have relied on typical occupancy profiles that give approximate levels of typical occupancy on an hourly basis. While data at this

resolution level can be very useful in roughly assessing the impacts on building systems that function with significant inertia, like heating and cooling systems, addressing concepts such as lighting energy use, water demand, and plug loads has lead researchers to attempt to provide finer resolution on such data, and then to further explore movement by attempting simulation algorithms.

Markov-Chains

When considering the movement of people in a space in occupancy models, once the models have been expanded beyond deterministic schedules, the way in which the occupants move must be considered. A common way of handling this type of modeling is to use a Markov-chain analysis. A Markov-chain is a mathematical analysis tool that mimics a discrete-time random process, such as the movement of occupants in a building. At each time step, a space can be in various states of occupancy, and the state of occupancy during the next discrete time step is dependent only on the current state of occupancy, known as a first-order process. When considering a single-occupant office, for example, there exist only two occupancy states: occupied and unoccupied. During the next time step, the space may transition to occupied or unoccupied, and the likelihood of that transition is based only on the current occupancy state. An occupied office can either stay occupied or become unoccupied; conversely, an unoccupied office can either stay unoccupied or become occupied. The likelihood of an occupied space remaining occupied, for example, is a state change probability.

Stochastic Models

A recent simulation method by Page et al. (2008) provides the framework and validation for an occupancy model. The model was developed and validated for an office building, using data from the LESO-EB building in Switzerland. The model employs a Markov chain-based

analysis method and relies on stochastic decision making, as opposed to the traditional

deterministic decision making models used in previous works (refer to Page et al. 2008 for a

summary of previous occupancy simulation methods and their shortcomings).

To develop the model, Page et al. created a framework for analyzing the probability of an

occupant arriving, leaving or exhibiting short periods of absence from actual occupancy data,

which was collected using binary occupancy sensors and therefore provides no information

regarding the absolute level of occupancy. These probabilities were then incorporated into a

Markov-chain model, which also included information regarding the probability of long term

absences, such as vacations, thereby providing another distinguishing feature beyond other

occupancy models.

The model is executed in the Matlab technical computing environment. To establish the

model's parameters, the authors gathered occupied/not-occupied status information for various

spaces throughout the building. These data sets were then combined to create presence

probability profiles, which state the probability that an individual space is occupied in 15-minute

increments. For actual execution of the model, the authors created twenty distinct weekly

presence probability profiles, each in 15-minute increments. At the execution of each week of

the annual simulation, one of the twenty presence probability profiles is randomly selected. The

model assumes a first-order Markov process, where the current state of occupancy is dependant

only on the immediately-previous state of occupancy, as shown in Equation 1:

$$P(X_{t+1} = i | X_t = j, X_{t-1} = k,.., X_{t-N} = 1) = P(X_{t+1} = i | X_t = j) =: T_{ij}(t) \qquad \text{Eq. 1}$$

where X_t is the state of presence (occupied or unoccupied) at time step t, and i, j, and k are state

indicators where 0 represents unoccupied and 1 represents occupied. T_{ij} is the state transition

probability, which in this case of binary states, includes four options: T_{00} which is the probability

of an occupied space remaining unoccupied, T_{01}, which is the probability of an unoccupied space

becoming occupied, T_{10} is the probability of an occupied space becoming unoccupied and T_{11} is

the probability of an occupied space remaining occupied. It is also convenient to note that with

this simple first-order inhomogeneous Markov-chain process, the only two possibilities for an

unoccupied space is to either remain unoccupied (T_{00}) or become occupied (T_{01}). Likewise, the

only two possibilities for an occupied space is to remain occupied (T_{11}) or become unoccupied

(T_{10}). Mathematically, then, this can be represented in Equations 2 and 3:

$$T_{00} + T_{01} = 1 \qquad\qquad\text{Eq. 2}$$

$$T_{11} + T_{10} = 1 \qquad\qquad\text{Eq. 3}$$

This is considered a first-order inhomogeneous Markov process since the current

occupancy state is based only on the previous occupancy state, hence "first-order", and where the

state transition probabilities vary at each time step, hence "inhomogeneous." While the use of

this first-order inhomogeneous Markov process is based solely on the transition probabilities, the

authors included what is referred to as mobility parameter, μ, to account for the inherent

variations in human behavior. This mobility parameter is, at each time step, defined as the ratio

of a change of state presence to that of no change. Mathematically, the mobility parameter used

in this model is described by Equation 4:

$$\mu = \frac{T_{01}(t)+T_{10}(t)}{T_{00}(t)+T_{11}(t)} \qquad\qquad\text{Eq. 4}$$

When used in the model, the mobility parameter is selected as a static value which was

determined from the actual data, but selected randomly to apply to the full data set. A series of

twenty mobility parameters were calculated by the algorithm's authors based on the actual

observed state transition probabilities and are presented on a full-week basis in 15-minute

increments as well. However, when actually employed in the algorithm, the average value of

one of the twenty profiles is selected and used, instead of varying the mobility parameter in 15-minute increments throughout the year.

Incorporating the mobility parameter, the two main state transition probabilities are determined as shown in Equations 5 and 6:

$$T_{01}(t) = \frac{\mu-1}{\mu+1}P(t) + P(t+1)$$

<div align="right">Eq. 5</div>

$$T_{01}(t) = \frac{P(t)-1}{P(t)}\left[\frac{\mu-1}{\mu+1}P(t) + P(t+1)\right] + \frac{P(t+1)}{P(t)}$$

<div align="right">Eq. 6</div>

where *P(t)* is the probability of presence at the current time step and *P(t+1)* is the probability of presence at the next time step. The remaining two state transition probabilities are determined using the reciprocity illustrated previously.

To execute the model, the state transition probabilities are determined at each unique time step. A process known as Inverse Function Modeling (IFM) is used to evaluate the actual action. The IFM process essentially relies on the selection of a uniform random number between 0 and 1, and evaluates that variable against the cumulative distribution function (CDF) of the desired variable to determine whether or not an action has taken place. For example, if the state transition probability was determined to be 47%, and the uniform random number generator resulted in any number of 0.47 or lower, than the state transition is determined to occur. If the uniform random number generator resulted in any number above 0.47, the state transition is determined to have not occurred. Note, though, that the state transitions can refer to no change in occupancy or a change in occupancy, depending on the variable.

At the beginning of each simulated day, the probably of the occupant exhibiting a period of long-term absence is first assessed. This is done using a probability distribution function that remains static throughout the year and is assessed using the same IFM process described above. If the occupant is found to be on a long-term absence, they are assumed absent for the full day.

Otherwise, if they are found not to be in a period of long-term absence, the daily profile is determined.

Execution of the model requires the input of the number of individual zones, which are assumed to be single-occupancy, thus modeling the rates of occupancy for individuals. Additionally, the model requires the input of the simulation year. The simulation output provides a text file which gives occupancy status, 0 for unoccupied or 1 for occupied, in 15-minute intervals for an entire year. The model code provided also has built-in functions to provide information histograms reporting occupancy rates, and can additionally simulate multiple buildings, though none of those features were used for this work.

An example of a single occupant pattern is shown below in Figure 14. As shown in this single week, the occupant took a consistent lunch break on three of the five weekdays. On Monday, the occupant was only in during the morning hours, and on Tuesday the occupant spent much more time in their space. There was no occupancy on Saturday or Sunday.
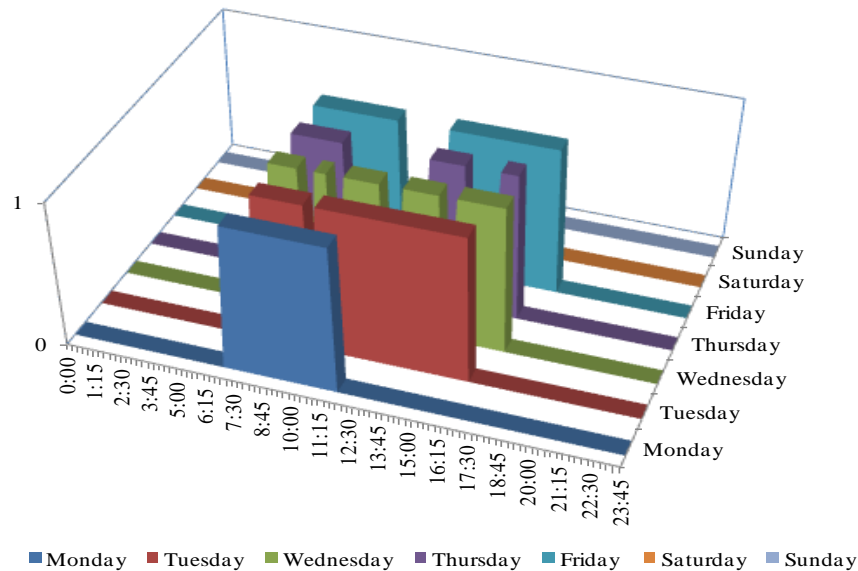
Figure 14: Single week occupancy pattern of a single occupant resulting from the Page et al. model, where 1 indicates that the office is occupied, and 0 unoccupied.

Combined Occupancy and Lighting Models

Previous research in the European community (Richardson, Thomson, & Infield, 2008) has integrated this type of stochastic occupant-based simulation into energy predictions for the residential sector. This modeling effort was based on simulated occupancy using a first order inhomogeneous Markov-chain simulation which accounted for variations between weekdays and weekends, and which was derived from self-reported data from the test subjects. This research provided the most robust capability for modeling time-based occupancy in a residential setting to date due to its inclusion of non-deterministic occupancy patterns. Another European research effort (Widen, Nilsson, & Wackelgard, 2009) combined Markov-chain simulations of occupancy patterns with stochastic predictions of lighting controls usage, incorporating the impact of daylighting, for residential environments. The goal of that effort was to understand the potential for the integration of photovoltaic (PV) systems into the residential power grid, since the availability of electricity from PV is typically not concurrent with the demand for lighting energy.

On the commercial building side, it has been shown that including the impact of occupant controls actually serves to reduce the potential savings for daylight-responsive electric lighting controls (Parys, Saelens, & Hens, 2009). Without the inclusion of occupant interaction, daylighting controls are often assumed to operate ideally, resulting in the maximum lighting energy savings. However, introducing the stochastic, or more precisely, imperfect, behavior of humans results in a reduction of expected savings. This finding is key when considering a priori cost-benefit analysis for lighting controls projects and for utility-level analysis of the appropriateness of incentives and system rebates.

More recent work (Mahdavi & Proglhof, 2009) focused on occupant interactions with controls in office settings, and found that, in general, it is very difficult to predict occupant interaction on a person-by-person level, but that on a building-wide or system-wide level, correlation could be found between energy use and environmental factors. Collected over multiple buildings with various daylight availability (including orientations), interior configurations and uses, the authors examined occupancy and lighting energy use profiles, and determined switching potentials for lighting controls, documenting the stochastic nature of the user/control relationship.

Another recent research effort in Europe (Saelens, Parys, & Baetens, 2011) introduced occupant modeling into commercial building energy simulations. This effort employed a Markov-chain lighting controls algorithm that was derived for private office spaces in the Lightswitch-2002 model (Reinhart C. , 2004). Additionally, the authors expanded the capabilities of blind control modeling from the Lightswitch-2002 model to include additional definitions of user types as they relate to blind controls. This model was then used to compare the energy performance of a thermally-activated building system (TABS) to a conventional cooling system, accounting for user interaction. For this situation with high system inertia, it was found that the overall occupancy rate had the largest influence on energy performance and that the intermediate arrivals and departures were less impactful. However, for systems like lighting that have the potential for large instantaneous changes, intermediate occupancy changes were more impactful.

Finally, Haldi & Robinson (2010) investigated the use of stochastic simulations to evaluate building energy use accounting for user interactions with shading devices and indoor temperature controls. They concluded that the recommendations that result from simulations

that include occupant behavior predicted in a stochastic manner are much more robust than recommendations that result from deterministic scheduling, which were "wholly unrepresentative of reality."

METHODOLOGY

The goal of this research effort was threefold. First, the use of the Page occupancy model as an input to a modified version of the Lightswitch-2002 model was studied to determine the impact of the various parameters on the resultant energy use and to explore the ability of the model to simulate data found from an actual sub-metered building. Second, limitations of the models were explored and additional model parameters were evaluated. Finally, recommendations for large-scale occupancy-related data collection efforts were provided to assist with ongoing research goals to transition to a true energy baseline in various lighting energy codes. This overall process was designed to answer the question: How do we begin to include a performance-based lighting energy analysis approach that incorporates natural human variation to support a transition to lighting energy as the basis for regulation?

In support of the first goal, the Lightswitch-2002 model was examined with regards to its limitations. Currently, the model is limited to private offices, as the probabilistic switching functions are derived, in general, from studies of private offices. This behavior is not likely to be directly extendable to spaces that function differently, where occupants do not necessarily feel 'ownership' over their lighting controls or blinds. Therefore, it was a necessity for this effort to group various spaces by the likely level of 'ownership' and occupancy duration, and decision-making algorithms were adjusted to analyze this impact.

Though further developments with regard to manual blind operation have been published, the simple deterministic model used in the original Lightswtich-2002 model was used for this research effort. The development of that model (Haldi & Robinson, Adaptive actions on shading devices in response to local visual stimuli, 2010) was based on the private office paradigm as well, but was also tied directly to the type of shading devices (button-controlled shades) and

window configuration (upper/lower windows). The method in which the action probabilities are determined using their algorithm is through the use of empirically-based coefficients that incorporate the previous blind status, interior illuminance, and exterior illuminance. Performing a sensitivity analysis on those coefficients is not logical since modification of the simple coefficients is not justified without availability of additional data sets. Unlike the Page model, the Haldi & Robinson blind model does not have a free variable to assess as a part of the sensitivity analysis. Instead, recommendations for future data collection efforts in this area needed to focus on a complete secondary project, similar to the data collection effort required to gather empirical occupancy data to extend the Page model, to evaluate the response of occupants to the same parameters in different space types, in different locations, and with different types of shading and window configuration, though that added effort level may be beyond any currently budgeted project.

The way in which the dampening coefficients were mathematically applied to the action probability varied based on the exact parameter being modified. For 'switch-on' actions, the identified "Active" user action curve was assumed to represent the highest degree of control. The dampening coefficient, therefore, increased the likelihood of a 'switch-on' event at each illuminance level until the distribution reaches that of the "Passive" user which does not consider daylight. For both of the intermediate action curves, the dampening coefficient served to reduce the probability of an intermediate action to zero at all conditions at its highest value. For the 'switch-off' actions, the dampening coefficient will also be used to reduce the probability of action to zero for all time durations.

The input parameters of the combined Lightswitch/Page model were then analyzed based on a sensitivity analysis assessing the Sensitivity Index, S_i, and Total Index, S_T, of each variable

to determine their contributions to the overall variance of the model (Saltelli, Tarantola, Campolongo, & Ratto, 2004). This included examining the input parameters with regard to action probabilities, including the dampening coefficients used to assess the impact of various levels of "ownership," as well as the mobility parameter from the Page occupancy model. This method of sensitivity analysis allowed for two important pieces of information to be determined. The S_i determined for each free variable describes the sensitivity of the model to only that variable, ignoring the effect of variable interactions. The Sensitivity Index is useful to assess whether or not the model is additive, where the total variance of the model can be directly accounted for by individual variables without subsequent interaction. The Total Sensitivity Index determined for each free variable describes the sensitivity of the model to that variable and its interaction with the other free variables. The Total Sensitivity Index allows for a percentage of the total variance of the model to be assigned to each individual variable.

The two combined models, Page and Lightswitch, were then used to evaluate their ability to predict lighting energy use by comparing the results of the simulation to a set of sub-metered lighting energy data from an office building in Minnesota. Based on this analysis, the appropriateness of the models and their ability to accurately capture the lighting energy use in the building was evaluated. This included the ability of the model to match the annual energy use, hourly energy use and hourly peak demand.

The results of these first efforts allowed the model to be evaluated against empirical data. During this evaluation, the shortcomings of the overall model were identified and additional model variations to overcome those shortcomings were proposed and evaluated.

This overall analysis process provided results which can be used to inform future efforts of data collection in an effort to provide a more complete modeling capability that includes all

interior space types that are regulated under building energy codes. The final phase of this work

involved constructing a series of recommendations for future data collection that will allow those

efforts to be concisely focused on providing useful data. Since the data collection efforts will be

cost constrained, it is important to maximize their effectiveness, so guidelines are presented for

maximizing the efficiency of those future efforts based on the identification of the important and

unimportant input parameters.

INITIAL MODELING

The initial modeling phase included the alteration of the two models, Page et al. (2008) and Lightswitch-2002 (Reinhart C. F., 2004), and three methods of analyzing their performance, a comparison to deterministic schedule-based modeling, the sensitivity analysis and the validation effort.

Manual Control Algorithm

The base manual control algorithm used for this effort was the Lightswitch-2002 mode (Reinhart C. F., 2004)l. This model is well established in the simulation industry, as demonstrated through its continued incorporation into multiple simulation programs, such as ESP-r (Bourgeois, Hand, Macdonald, & Reinhart, 2004), and other research efforts such as those by Bourgeois, Reinhart & Macdonald (2005). This algorithm provided that necessary individual variation which was a goal of this research effort, but did so in an established method. However, due to the shortcomings identified, a few modifications were made to that base algorithm, which are discussed below.

Base Assumptions

In general, the base assumptions included in the Lightswitch-2002 model applied to this modified version. It was assumed that offices were single occupancy. It was also assumed that the "Active" and "Passive" user types existing, however additional users were included as described below.

Additionally, the simple blind control model from the Lightswitch-2002 model was used with minor modifications. This model assumes a binary blind condition: either fully open or fully closed. At the beginning of each day, the blinds are reset to the open position regardless of

their position at the end of the previous day. Additionally, the blind-closing threshold was

updated to align with the Useful Daylight Illuminance (UDI) metric, and thus the blinds were

closed when the workplane illuminance exceeded 2,000 fc.

Addition of Intermediate Switch-Off Actions

The base Lightswitch-2002 model included intermediate switch-on actions, where the

lighting was activated while the space was already occupied, typically due to a change in

daylight availability. However, the base model neglected to include intermediate switch-off

actions because of the observed variability of these actions. However, it is intuitive that typical

occupant behavior would likely include intermediate switch-off actions, though at a rather low

occurrence. Fortunately, additional data sets examining exactly this type of action are available

from other studies (Lindelof & Nicolas, 2006) and were incorporated into this effort.

Alteration of Intermediate Switch-On Action Basis

The base Lightswitch-2002 model relied on the intermediate switch-on action probability

as determined in the work of Reinhart & Voss (2003). However, the step-function applied to

these results provides a poor curve-fit, and appears to have been forced based on the author's

assumption of the general characteristic of this type of behavior. Discussion with one of the

authors confirmed the suspicion that the curve fit for this action was very poor. Based on that

author's recommendations, the intermediate switch-on action curve was changed to the results

from the Lindelof & Nicolas (2006) work.

Time-Series Adjustment for Probabilistic Actions

It is important to note that the reported action probabilities for the various lighting

actions, such as switch-on at arrival or intermediate switch-on, are derived from time-series data.

However, for the most part, the time step used to determine the action probabilities was not the

15-minute time interval that was the basis for the occupancy algorithm and thus the desired basis for the lighting action algorithm.

To correct this, the reported action probabilities were adjusted to account for the difference in time intervals. This was accomplished by assuming a continuous time-to-event problem assuming a survival function. In this case, the hazard function was assumed to be constant, and thus the survival function was a decaying exponential. The transformation was accomplished using Equation 7:

$$p = 1 - exp(\frac{T_1}{T} log(1 - p_1))$$
<div align="right">Eq. 7</div>

where p is the event probability after the time step transformation, T_1 is the original time step, T is the desired time step, and p_1 is the original probability. Using this method, the individual action probabilities were adjusted to align with 15-minute time increments.

Addition of Dampening Coefficients

The base Lightswitch-2002 model included two user types as defined previously: an "Active" user who takes daylighting into account and may be more aware of their lighting energy use leading to variations in the switching action probabilities; and a "Passive" user who essentially does not take any ambient lighting conditions into account and whose switching actions are based solely on arrival and departure events. In general, these were assumed to be the extremes of behavior.

For this effort, it was desirable to include a gradation of user types to explore whether modeling with only two distinct populations is sufficient to account for various user types. This was achieved through the use of dampening coefficients. Based on the known switching action probabilities, the "Active" user was assumed to have a dampening coefficient of 0; essentially, their behavior is assumed to be as energy-aggressive as possible. The "Passive" user was

assumed to have a dampening coefficient of 1; essentially their interaction with the daylighting was dampened until it became nonexistent.

Dampening coefficients were then applied linearly at each triggering value, illuminance or time, to provide a gradation of user behavior. This gradation can be interpreted as an attempt to model users of varying degrees of daylight sensitivity. They may, for example, account for users with visual disabilities or of older populations, who are energy aggressive but require higher general light levels than the assumed "Active" user.

The dampening coefficients were then applied to each of the four action curves to create a spectrum of users. When actually employed in the model, the dampening coefficients were structured to be infinitely variable between 0 and 1, allowing for fine tuning of user types. Figure 15 through Figure 18 illustrate the incorporated adjusted action probability curves along with the dampening coefficients.
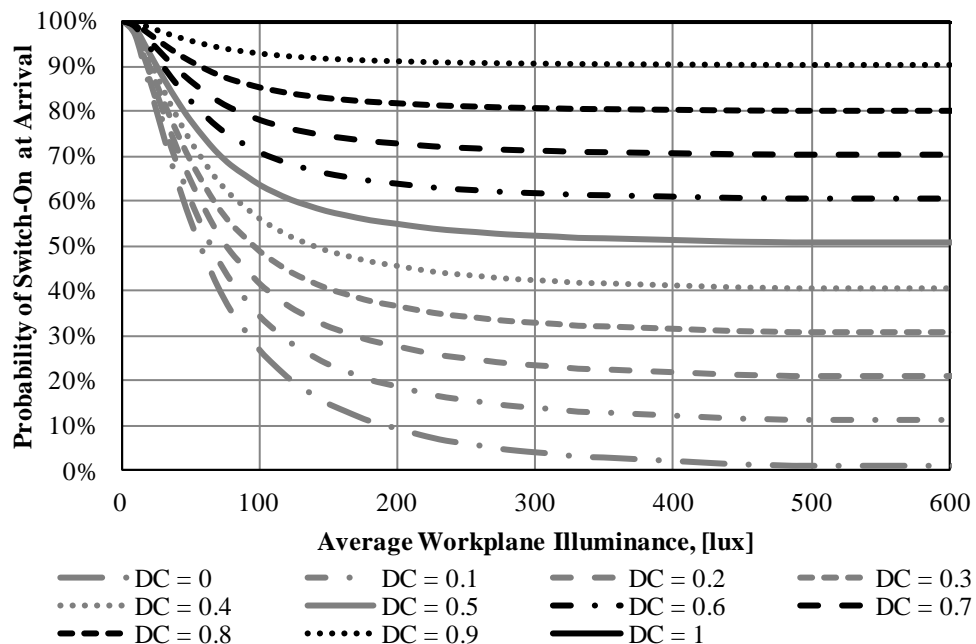
Figure 15: Probability distribution function for switch-on at arrival as a function of average workplane illuminance including dampening coefficients.

As shown in Figure 15, for the probability of switch-on at arrival, a dampening coefficient of 1 results in the "Passive" user definition, which is interpreted as a user who activates their lighting upon arrival independent of the workplane illuminance, thus the constant $p = 1$. The dampening coefficient of 0 follows the transformed function of an "Active" user. The dampening coefficients were created using linear interpolation at each illuminance level between dampening coefficients, though when actually employed, the dampening coefficients are infinitely variable.
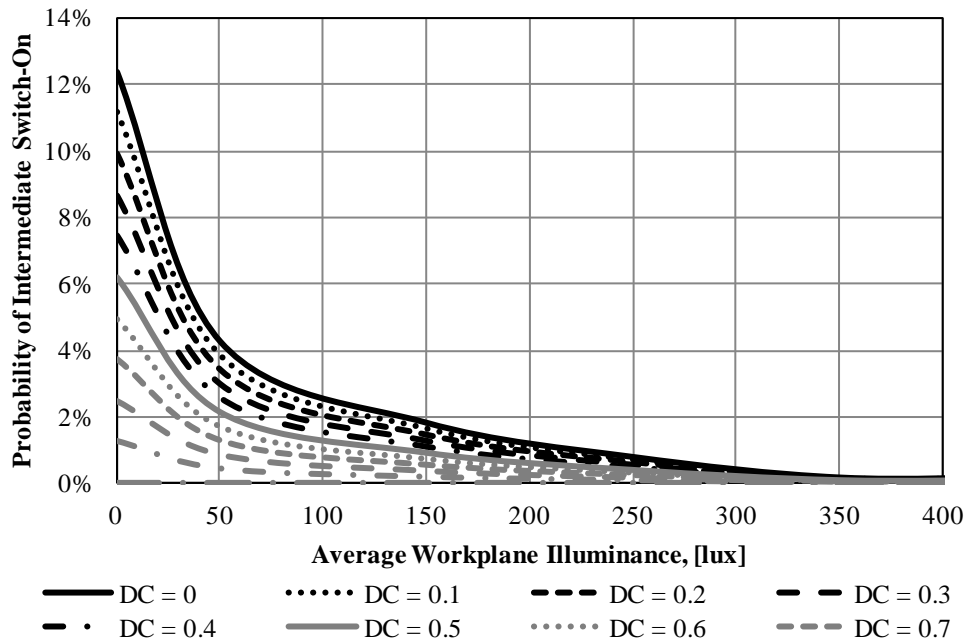
Figure 16: Probability distribution function for intermediate switch-on as a function of workplane illuminance including dampening coefficients.

Figure 16 illustrates the employed probability functions for intermediate switch-on actions. As described above, the base action probability function assumed in the Lightswitch-2002 model was a step function that was felt by the author of that function to be somewhat forced. Therefore, the employed action probability curve was based on the results of the study with a much larger data set (Lindelof & Nicolas, 2006), which showed a decaying function with

respect to increasing workplane illuminance. In this case, the dampening coefficient of 0

represents the "Active" user who is most responsive to ambient daylight conditions. Likewise, a

dampening coefficient of 1 represents a "Passive" user who does not engage in any intermediate

switch-on actions. As shown though, even at the lowest illuminance level, the probability of an

intermediate switch-on action was only around 12%. Above approximately 50 fc, which would

be considered the high-end of interior office lighting recommendations, the probability of an

intermediate switch-on action drops below 5%.
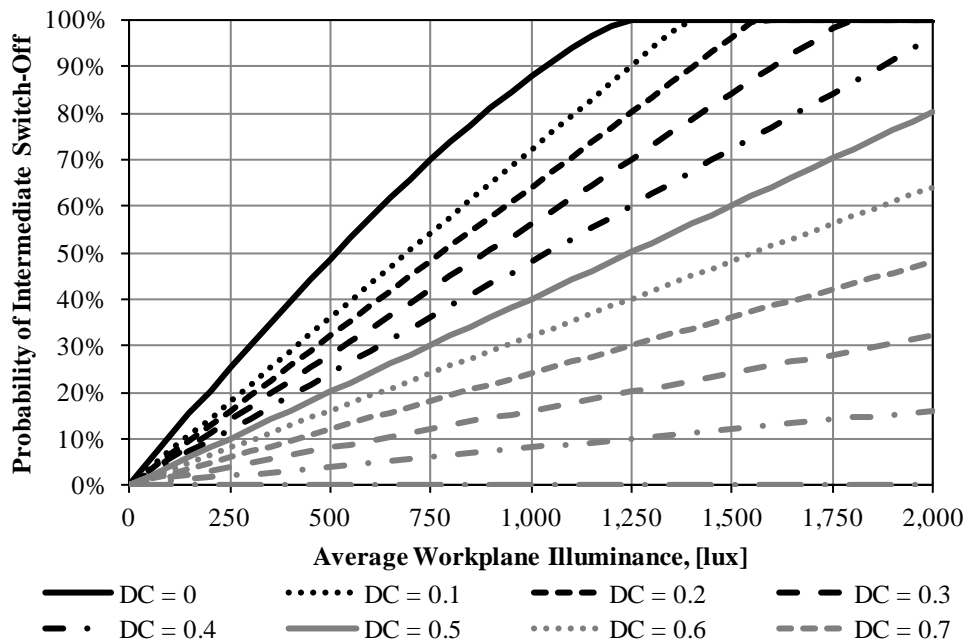
Figure 17: Probability distribution function for intermediate switch-off action as a function of workplane illuminance including dampening coefficients.

Figure 17 illustrates the adjusted probability of intermediate switch-off action as a

function of average workplane illuminance. Again, the inclusion of any intermediate switch-off

action can be considered a major modification to the base Lightswitch-2002 algorithm. Again, a

dampening coefficient of 0 indicates an "Active" user who is most likely to engage in

intermediate switch-off actions overall. For that user type, the probability of an intermediate

switch-off action is reduced to zero as the average horizontal workplane illuminance is also decreased. Once the workplane illuminance reaches an excess of 1,250 fc, the probability of a switch-off action equals unity.

It should be noted that the illuminance scale for intermediate switch-off actions is shifted significantly higher than for intermediate switch-on actions. Essentially, at typical interior light levels of 250 fc and below, the probability of an intermediate switch-off action is less than 30% even for the most active user. These curves were only extended to 2,000 fc assuming that the model was adjusted to include blind controls based on the UDI range, which would set a maximum cap here of 2,000 fc before the blinds are drawn and the sole source is the electric lighting.
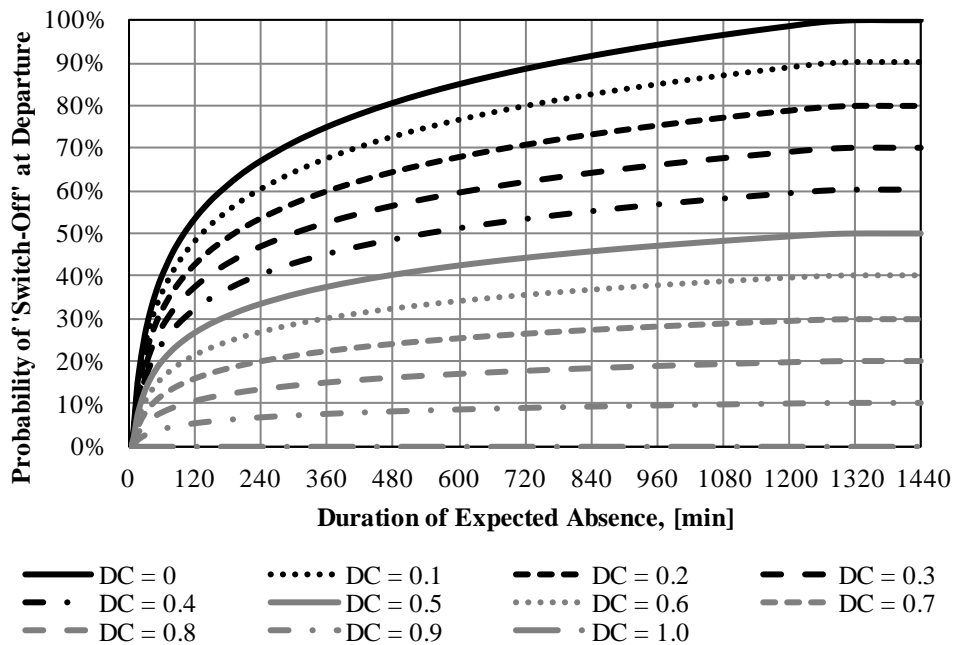
Figure 18: Probability distribution function for switch-off at departure as a function of expected duration of absence including dampening coefficients.

Figure 18 illustrates the adjusted probability of switch-off at departure as a function of the duration of the expected absence. As shown, as the expected absence approaches a full day

(24 hours), the probability of a switch-off at departure by an active user approaches unity. The impacts of the dampening coefficients are shown, but it is important to understand their applicability and limitations. For the sensitivity analysis, it was important to evaluate the sensitivity of the overall model combination to the probability of a switch-off at departure, so the ability to control dampening coefficients was included. However, when tuning the model during the validation efforts, the dampening coefficients for this action probability curve were typically left equal to zero. Essentially, the dampening coefficients were meant to capture the variability of behavior with respect to daylight availability. Since the independent variable here is duration of expected absence, the inclusion of the dampening coefficients did not work toward exploring the impact of daylight-responsive behavior. Therefore, the dampening coefficients were not strongly employed during the validation efforts.

Automated Control Algorithm

To construct as feature-rich a model as possible, it was important that the model include the integration of automated controls behavior. The ability to simulate both automated occupancy-based and automated time-based controls were included.

Time-based Controls

The most simple of the automated controls are time-based. For this modeling effort, time was counted in 15-minute increments, so it was assumed the same granularity applied to the controls operation. Therefore, simulations involving time steps other than 15 minutes for lighting controls were not possible.

The ability to integrate time-based automated controls along with manual controls was also extremely important. Many automated lighting system controls rely on what are known as "vacancy sensors," or manual-on occupancy sensors. Vacancy sensors require the user to

activate the lighting, but then extinguish the lighting after a certain pre-set time period of inactivity is detected. Therefore, the simultaneous integration of manual and automated controls was very important.

Occupancy-based Controls

Occupancy-based controls tie directly into occupancy patterns. Typical occupancy sensors will activate the lighting when an occupant is sensed, and extinguish the lighting after a certain pre-set time period of inactivity is detected. To make the modeling capability as feature-rich as possible, the models were constructed to have the ability to model these types of automated controls, though they are less typical in the market than vacancy sensors.

Daylighting Controls

It was a desire to integrate automated daylight-responsive switching and dimming into this effort. However, after further exploration, providing that capability was beyond the scope of this project but should be considered highly important in future advancements. As noted in the actual simulation code provided, the inputs were structured to include the possibility for automated daylight dimming and switching, though no actual functionality was included.

Occupancy Algorithm

The occupancy algorithm used for this process was the base Page algorithm described in detail above. This algorithm was adjusted to simply feed annual binary occupancy pattern data streams into the modified Lightswitch-2002 model for analysis. The occupancy model was executed in one of two ways depending on the goal of the analysis.

First, the occupancy algorithm was structured to allow it to rely on the built-in randomized selection of one of twenty mobility parameters. Second, the model was modified to allow the mobility parameter to be controlled as a "free variable." This allowed the impact of the

mobility parameter to be explored during the sensitivity analysis to quantify the contribution of

the mobility parameter to the variance of the overall model contribution. However, the authors

of the occupancy model indicate that the mobility parameter should be set values, so exploring

what those values were and how they influence the model results was also of interest.

Model Flow and Environment

The overall model combination was designed and executed in the Matlab technical

computing language. The Page occupancy model was received in this format by one of the

authors. The modified Lightswitch model was also created in Matlab. Full code is included in

Appendix A.

Speaking generally, the model input values include:

- Year (e.g. 2011);

- Number of zones (or people);

- Target illuminance in lux;

- Installed lighting power density in W/sf;

- Control system type:

  o 1 = Manual On/Manual Off, No Daylighting

  o 2 = Manual On/Auto Off, No Daylighting

  o 3 = Auto On/Auto Off, No Daylighting

  o 4 = Manual On/Manual Off, With Daylight Dimming

  o 5 = Manual On/Auto Off, With Daylight Dimming

  o 6 = Auto On/Auto Off, With Daylight Dimming

  o 7 = Manual On/Manual Off, With Daylight Bi-Level Switching

- o 8 = Manual On/Auto Off, with Daylight Bi-Level Switching

- o 9 = Auto On/Auto Off, with Daylight Bi-Level Switching

- o 10 = Bi-level (50% Auto On, 50% Manual On/All Auto Off, No Daylight

- Delay time for occupancy or vacancy sensor in 15-minute increments; and

- Blind control type where:

  - o 1 = fully manual open/closed

  - o 2 = fully automated ideal control.

The execution begins with the occupancy model for all occupants, so for example if 20 offices were simulated than those 20 occupancy profiles were generated first. The modified Lightswitch model was then called and each individual occupancy time series fed through that second model to calculate annual lighting energy use.
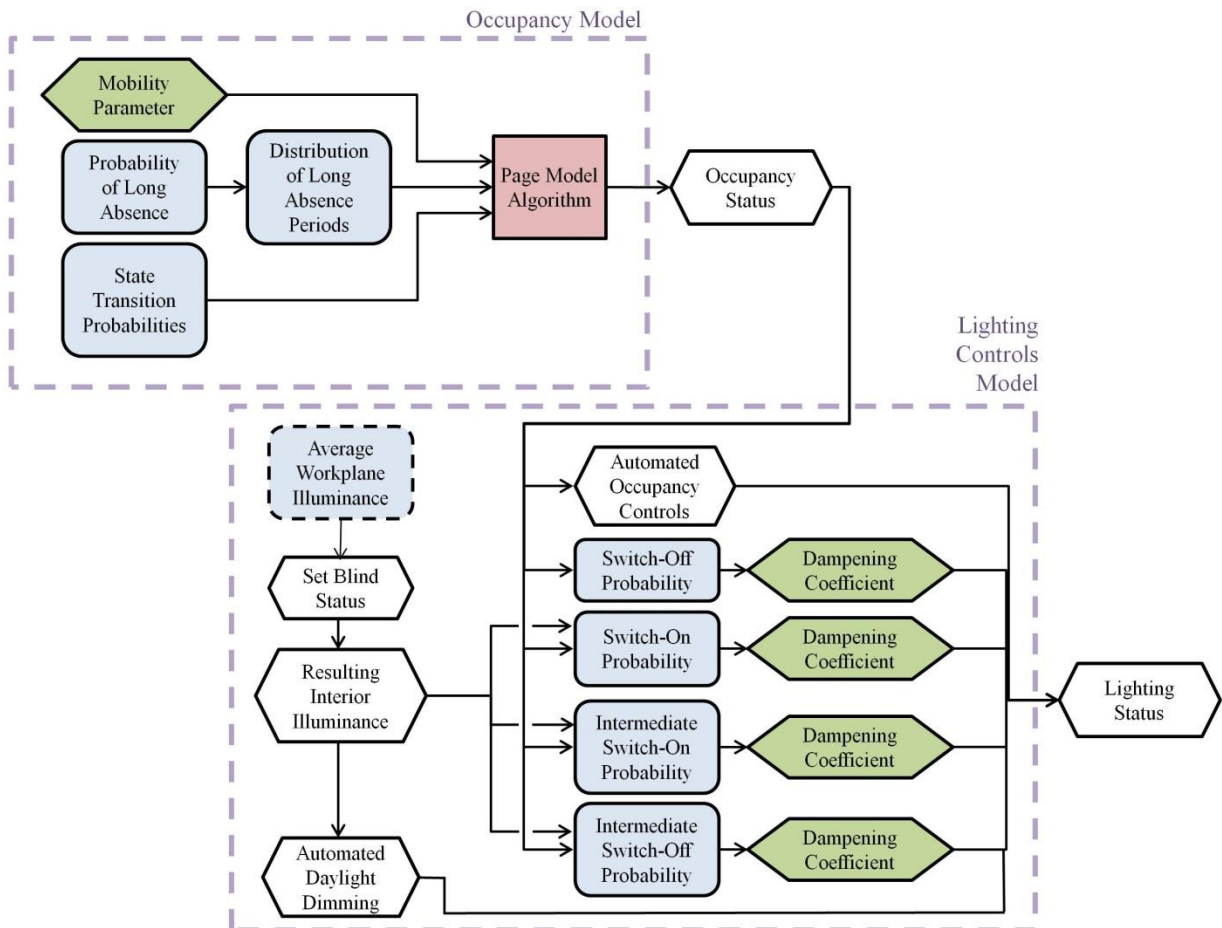
Figure 19: Flowchart illustrating combined occupancy and lighting controls model.

Dampening coefficients for each user were loaded as text files, allowing each occupant to be assigned their own set of dampening coefficients to model the possible array of users across offices. Additionally, horizontal workplane illuminance values from the daylighting simulation were loaded as a text file, with the ability to provide different patterns for each room to allow the simulation of building diversity.

Subject Building Information

To conduct this analysis, an actual office building was selected in near Minneapolis/St. Paul, Minnesota. This building was designed with advanced green building strategies, including

indoor air quality (IAQ) monitoring, geothermal heat exchange, and thermal energy storage. The

lighting design consisted of high-efficiency luminaires, coupled with advanced controls, and

designed with a lighting power density lower than that required by the applicable energy code

(ANSI/ASHRAE/IESNA, Standard 90.1-2004). Table 1 includes a breakdown of the various

space types within the building.

Table 1: Breakdown of various space types within the subject building.

Space Type	Area, [sf]
Private office	14,800
Open office	12,000
Conference	5,100
Corridor	9,100
Lobby	800
Storage	3,000
Mech/Elec	1,000
Restroom	1,300
Data center	600
Dining	2,800
Locker Room/Shower	700
Fitness Room	1,100
TOTAL	52,300

This building was designed to comply with ANSI/ASHRAE/IESNA Standard 90.1-2004.

Under that code, the allowable lighting power densities using the space-by-space method is 1.1

W/sf for the private, or enclosed, offices. Using the space-by-space method, the overall building

allowable lighting power is 52,950 W, or 1.012 W/sf. The minimum control requirements for

the private office spaces include the provision for at least one automatic control device that

extinguishes the lighting within 30 minutes of the space becoming unoccupied, where that

control device can be activated either manually or automatically based on presence. No

daylight-responsive controls were required.

In this sample building, the actual installed lighting power density in the private offices was only 0.87 W/sf, a 21% reduction over the code-maximum allowed. The installed lighting power in the whole buiding is approximately 52.3 kW, or 1.0 W/sf, which is high due to high energy use in non-office spaces. Additionally, the actual installed lighting control system in the private offices is slightly more advanced. In each space, the lighting is controlled via occupancy-based bi-level lighting controls. Essentially, 50% of the installed wattage is controlled using an occupancy sensor that automatically activates the lighting when the space becomes occupied. The remaining 50% is controlled using a vacancy sensor that requires manual activation. All of the installed wattage is extinguished after the space becomes unoccupied for 15 minutes. No daylight-responsive controls were installed, and manual blinds were used to allow occupant control over the daylighting.

In total, there were 74 private offices in this building and all have access to daylight and are approximately the same shape and size. Half of the offices were assumed to be North-facing and half South-facing.

WINDOW WALL ELEVATION
SCALE: $\frac{1}{8}$" = 1'-0"

FLOOR PLAN
SCALE: $\frac{1}{8}$" = 1'-0"
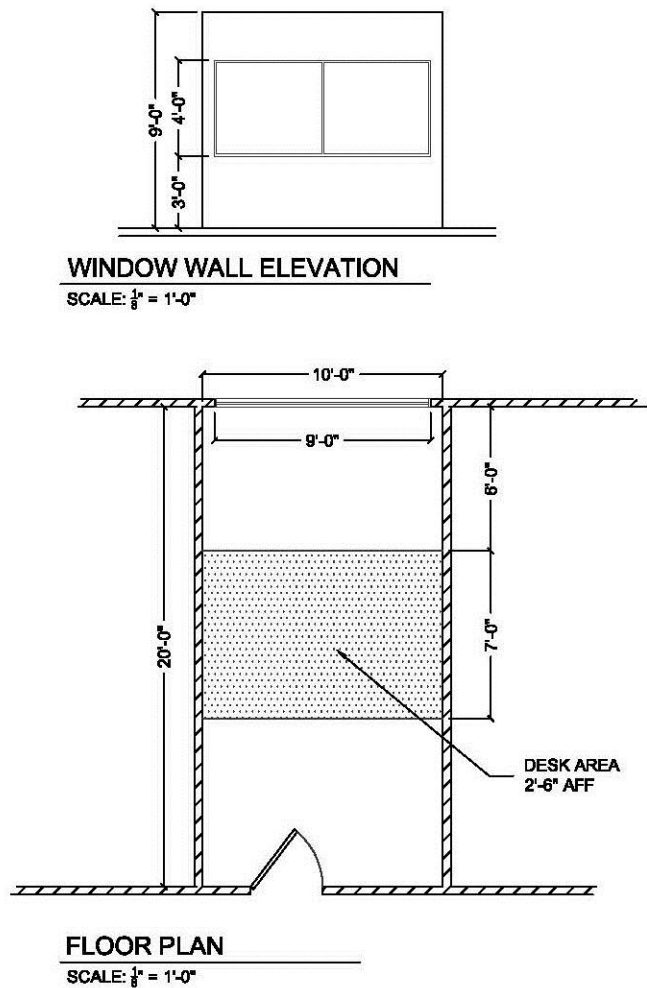
Figure 20: Floor plan and elevation of window wall of typical private office.

Data Filtering

Lighting energy within this building is sub-metered with ongoing power consumption reported on a website dashboard that allows users to view the effectiveness of any energy saving measure. For this analysis, the lighting energy data in one-hour increments was downloaded from the website, and spans a date range of 11/30/2008 to 6/21/2011.

The data available is for the full-building lighting, excluding the exterior lighting system, and only includes hard-wired lighting loads. There was no quality control of the measured data. This information was used directly for comparison to the results of the deterministic schedule

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analysis for the whole-building. To use the data for evaluation of private office lighting energy

use, as was performed with both the deterministic and stochastic models, the data was filtered

down to approximate the lighting energy use in only the offices. To perform this filtering, it was

assumed that the portion of the lighting energy consumed at each time that was attributable to the

private offices was of the same proportion as the installed lighting power in those offices to that

of the entire building. Therefore, the hourly data was filtered down at each time step using this

approximation.

While the actual lighting data is only directly comparable to the deterministic whole-

building simulations, it also provides interesting insight into the operational profile. Therefore,

the strongest comparison with this data is made to the whole building simulations. While this

distillation process assumes that all spaces within the building are functioning essentially on the

same type of occupancy profile, which is not likely to be exact, the overall pattern of occupancy,

and thus energy use, is interesting to compare to the assumed patterns of the advanced

simulations and deterministic schedules. However, there is a precedent for this type of

reductionary estimation in energy modeling where known aggregates of building occupancy data

are applied in simulation to specific space types; for example, a known office building

occupancy pattern based on aggregated data is applied to individual heating and cooling zones,

assuming that their occupancy patterns directly mimic that of the overall building. While this

does not necessarily justify the inaccuracy, it stands to reason that the same logic can be applied

to this effort with the same caveats.

Daylighting Model

A daylighting model was constructed using AGI32 software, a CIE-validated industry

standard lighting calculation software. AGI32 employs the radiosity method of interior

illuminance calculation, and includes the option for adaptive subdivision as a standard for daylighting calculations. Two rooms were constructed, one with its window facing North and one facing South. Both rooms were built assuming standard floor and ceiling reflectances (30%, 80%). The walls were assumed to have a reflectance slightingly higher than standard (70%) based on known information about the building. Horizontal illuminance points were located at the general desk area, were 2.5' above finished floor (AFF), and spaced 2' in both directions. The model coordinates were set for Avon, Minnesota (45.5°N, 94.5°W). It was assumed that there were no external shading devices. Windows were modeled to be transparent daylight transmission glass with a 50% visible light transmittance (VLT).

Refer to "Daylighting Calculation Assumption Exploration" below for more detailed information on the process for determining the available daylighting. For the convergence testing and sensitivity analysis, both where only a single user/room is simulated, it was assumed the space was South-facing. The Southern exposure results in the highest range of illuminances on the workplane, thus testing the more extreme use of the model.

Model Convergence

The first test performed on the entire model system was to test for model convergence on total annual energy use. The stochastic nature of both the occupancy and lighting controls models creates inherent, and desirable, variability in the model output. However, if the model values are to be useful, it is critical that the number of simulations necessary to reach a meaningful value be determined. This was executed first for only the occupancy model, assessing the mean annual predicted occupied hours. This process was then executed for the combined occupancy and lighting controls model to determine the number of simulations necessary to reach convergence on a total annual energy use.

Sensitivity Analysis

In order to begin to understand the sensitivity of the overall model combination to the various free parameters, a series of simulations were performed to the found convergence limit N where each of the five free variables was randomly varied. Scatterplots were created to review if any general trends were observable. To generate the scatterplot data, the simulation was executed assuming the full five possible free parameters, the four lighting action dampening coefficients and the mobility parameter. This analysis was performed using both the Reinhart and Lindelof intermediate switch-on action curves.

The Sensitivity Index of each parameter was first determined. The Sensitivity Index determines the fraction of the total variance of the model that is directly attributable to first-order effects of each variable, as shown in Equation 8:

$$S_i = \frac{VAR_i(Y)}{VAR(Y)} \hspace{3cm} \text{Eq. 8}$$

where S_i is the sensitivity index of parameter i, $VAR_i(Y)$ is the variance of the model Y due to variations in parameter i, and $VAR(Y)$ is the total variance of the model output Y.

To determine the Total Sensitivity Index of each free variable, the variance-based method published by Saltelli et al. (2010) was used. This method employs a Sobol' quasi-random sequence to vary the input parameters in the range [0,1], which uses a winding design to maximize computational economy. The Sobol's sequence is useful in that, unlike truly random number generators, the Sobol sequence uniformly covers the available number space for each input parameter in the range [0,1]. The analysis requires $N*(k+1)$ simulations, where N is the number of simulations needed to reach convergence and k is the number of free parameters. For each iteration, $k+2$ individual simulations are performed, with the input values of the free variables based on the Sobol' sequence. The first value is labeled as vector yA and the second

value is labeled as vector *yb*. The last *k* values are used to construct vector *yAb*. *y4var* is then

created as a vector containing *yA* and *yb*. Individual first-order variances V_i and higher-order

variances V_T are then determined using Equations 9 and 10 respectively:

$$V_i = yB(yAb(j) - yA) \ for \ j = 1:k \qquad \text{Eq. 9}$$

$$V_T = (yA - yAb(j))^2 \ for \ j = 1:k \qquad \text{Eq. 10}$$

Next, the total model variance V_{tot} was determined as the variance of the vector *y4var*. Finally,

the Sensitivity Index and Total Effect Index are calculated using Equations 11 and 12:

$$S_i = mean(V_i)/V_{tot} \qquad \text{Eq. 11}$$

$$S_T = mean(V_T)/(2V_{tot}) \qquad \text{Eq. 12}$$

The combined occupancy/lighting actions model was then evaluated using this detailed

sensitivity analysis. This analysis involved determining the sensitivity index, S_i, and total effect

index, S_T, for each "free" variable. In the first case, all five possible free variables were the four

dampening coefficients assigned to the lighting action probability curves and the occupancy

mobility parameter. Again, this was also performed separately for the models incorporating the

Reinhart and Lindelof intermediate switch-on action curves. Assessing the sensitivity of the

overall model results to these dampening coefficients in effect estimates the impact of the type of

user and their unique behavior on the overall model results.

For the second case, the mobility parameter values were fixed at pre-determined and

important values to allow the sensitivity of the overall model to the action probabilities to be

determined without including the influence of randomly-selected mobility parameters. In effect,

this second case provided more detailed analysis of only the lighting action curves and allows

comparison between the results of the impact of known pre-set mobility parameter values.

Comparison to Deterministic Scheduling

To evaluate the stochastic advanced models against the more standard, common and simple deterministic models, a simple comparison was performed, and was focused in two parts.

Whole-Building Evaluation

The first step was comparing the estimated lighting energy use, peak demand, and consumption profiles predicted through the use of deterministic scheduling to the whole-building unfiltered sub-metered lighting energy data. This analysis was performed both with a known energy-saving lighting power density, and with the default value allowed under the applicable energy code, ASHRAE/IESNA Standard 90.1-2004 (2004). Table 2 provides the full description of these seven simulation sets, illustrating the pairing of the lighting power densities with the schedule source.

Table 2: Description of simulation parameters for deterministic whole-building models.

Schedule Source	ACM		DOE-2		Business Hours	
LPD Source	Actual	90.1	Actual	90.1	Actual	90.1
Total LPD, [W/sf]	1.00	1.01	1.00	1.01	1.00	1.01

For this analysis, total annual energy consumption and peak demand were estimated using the applicable schedules for the subject building and compared to the results of the sub-metered data from that building.

Private Office Only Evaluation

Considering only the private offices, an analysis was then performed to assess the predicted annual energy use and peak demand through using both the deterministic schedules and the stochastic occupancy/lighting controls model, which applies only to private offices.

These results were compared to the sub-metered lighting energy data, which was filtered as described above to estimate the annual energy use and peak demand from only the 74 private offices. This again was performed using both the known installed lighting power density in the space and the maximum allowable under the applicable energy code. Table 3 illustrates these pairings, where the "AS" indicates the advanced stochastic simulations.

Table 3: Description of simulation parameters for deterministic and stochastic office-only modeling.

Schedule Source	AS1	AS2	AS3	AS4	AS5	AS6	ACM		DOE-2		Business Hours	
LPD Source	Actual						Actual	90.1	Actual	90.1	Actual	90.1
LPD, [W/sf]	0.87						0.87	1.1	0.87	1.1	0.87	1.1

For the six stochastic simulations, the dampening coefficients for the private offices were carefully selected to explore the direct impact of them individually and to understand potential equalities of settings. Table 4 shows those various settings. As noted previously, an "Active" user is assumed to have a dampening coefficient (DC) equal to zero for all action curves. A "Passive" user is assumed to have a DC equal to one for all action curves. Additionally, for this analysis, the standard "Active" action probability curve for switch-off at departure was used for all scenarios, including the "Passive" user definition. The main reason for limiting the use of the dampening coefficients to apply only to the other three action curves, switch-on at arrival and the two intermediate action curves, is that those three action probabilities are illuminance-based, whereas the switch-off at departure is time-based. The dampening coefficients are truly intended to explore a range of user types as they apply to awareness and interest in actively responding to their lighting needs with respect to daylighting conditions. The dampening coefficient applied to

the action probability curve for switch-off at departure was meant to be explored though other

avenues, such as the sensitivity analysis.

Table 4: Description of six stochastic user type distributions used to compare to the results of predictions based on deterministic scheduling.

Simulation	Description
AS1	All Passive Users
AS2	All Active Users
AS3	All DC = 0.5
AS4	50% Active / 50% Passive
AS5	All DC = 0.25
AS 6	All DC = 0.75

Initial Validation

The final step of this first phase of the analysis was to use the combined occupancy and

modified lighting action model to attempt a validation against the filtered sub-metered lighting

energy data as described above. To perform this analysis, first the annual daylighting profile for

each of the offices was determined as described later. Annual simulations were then performed

which included all of the 74 private office spaces, referencing text files that included arrays of

dampening coefficients. A single mobility parameter was included and applied to all 74 offices.

The results of the simulation were then compared to the filtered sub-metered data, both in terms

of annual energy predictions, and in terms of attempting to match daily profiles, including peaks.

The dampening coefficients and mobility parameter were then manually adjusted to attempt to

match the desired values, and the simulation then executed again. No optimization protocol was

used since the number of free variables within the model environment would require a

computationally-inefficient process. Instead, the individual parameters were adjusted by trial

and error, first adjusting the mobility parameter to scale the general use up or down, then adjusting each dampening coefficient to impact the rate of energy use increase in the morning (switch-on parameter), rate of energy use decrease at the end of the day (switch-off parameter), and during the intermediate occupancy periods (intermediate actions). Because of the interaction of the various parameters, no unique solution exists.

Model Convergence

The purpose of the first set of tests performed was to assess the number of simulations required to find convergence on the mean value.

Occupancy Model

First, model convergence was tested for the occupancy model alone. This test was based on the base model where the mobility parameter is selected within the algorithm using the built-in values and relying on the built-in randomizing function. Figure 21 illustrates the average annual occupied hours as a function of the number of simulations.
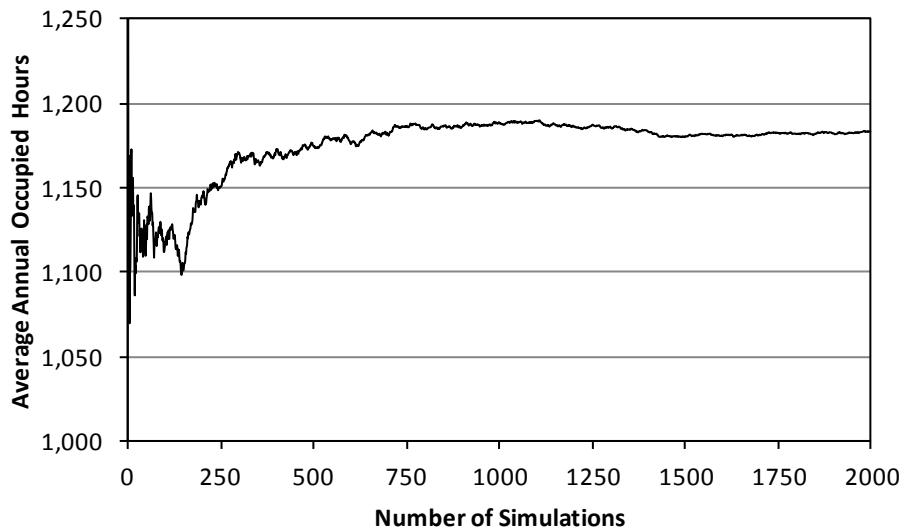
Figure 21: Model convergence for occupancy algorithm.

As shown, the initial results vary significantly due to the inherent variability of the stochastic model. It is not desirable to dampen this impact since the inherent variability is what makes this model valuable, but in this case it is important to understand how many simulations are necessary to reach a meaningful mean value. After the initial variability, the mean shows an

upward drift before settling to a regular value of approximately 1,184 hours per year. Assuming

a 40 hour per week work week and 50 days per year, this result shows an annual occupancy rate

of only 59.2%.

Figure 22 presents a histogram of the simulated annual occupied hours used to determine

the mean value as shown in Figure 21. While the model shows a clear central tendency near the

determined absolute mean value, there is also an evident trimodal distribution.
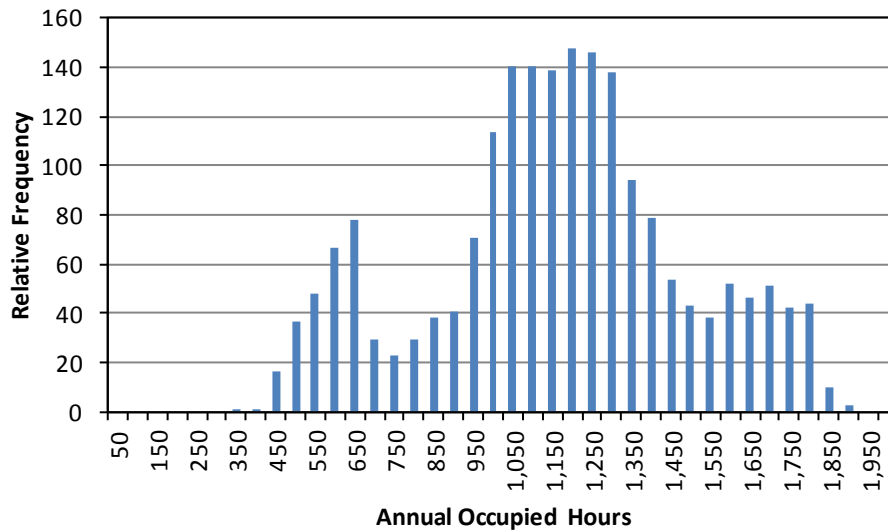
**Figure 22: Relative frequency of simulated annual occupied hours for occupancy
algorithm.**

Combined Occupancy and Lighting Model

The same process was executed for the combined model which included the unmodified

occupancy algorithm and the modified Lightswitch-2002 algorithm. For this analysis, it was

assumed that the dampening coefficient for all action probabilities was zero, which is the

definition of an "active" user who is most likely to engage in switching actions, and the default

mobility parameter method in the base occupancy algorithm was used. Figure 23 illustrates the

average annual energy use as a function of the number of simulations. For this analysis, the

simulation assumed a 200 sf private office with an installed lighting power density of 0.87 W/sf. The daylight conditions were assumed to be consistent with the South-facing office of the subject building. As shown, due to the stochastic nature of each of the combined models, there is initially large variation in the determined mean at a low number of simulations. As the number of simulations increases beyond 1,000, the variation in the mean became dampened. Based on the results of the occupancy analysis, it was determined that using 2,000 simulations would result in sufficient convergence.
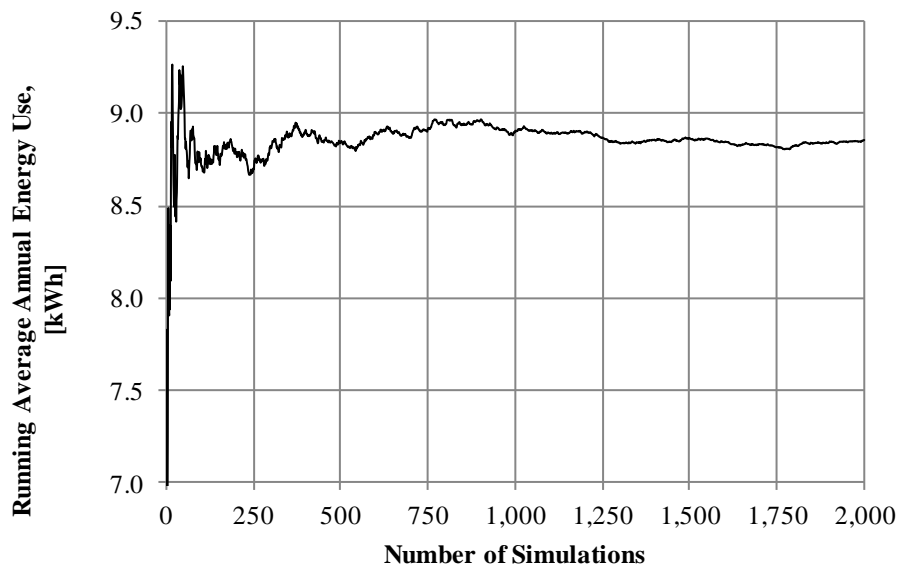
Figure 23: Model convergence for combined occupancy and lighting control algorithm.

Likewise, Figure 24 illustrates the relative frequency of the simulated annual energy use for the combined occupancy and lighting controls model. As shown, the trimodal distribution of the occupancy simulation is dampened by the inclusion of the lighting controls model, and therefore the combined model does not exhibit that same type of trimodal distribution. The highest concentration of simulation results occurred in the $8 \text{ kWh} \leq Y < 9 \text{ kWh}$ band, which correlates with the determined mean.

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The distribution of the data is skewed with a long right-hand tail. This skew is due to the low-end limitation at zero that can physically be interpreted as no annual lighting energy use; a negative number is not feasible, nor realistic. High annual energy use, reaching upwards of 20 kWh/year, skew the distribution to the right and are due to the stochastic nature of the switching actions which can result in lighting being left "on" over nights and over weekends or longer holidays.
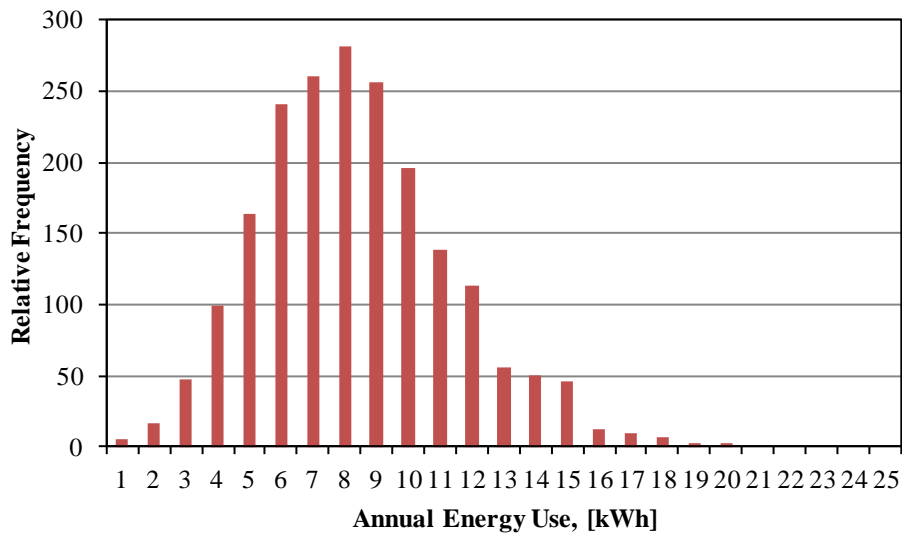
Figure 24: Relative frequency of simulated annual energy use for combined occupancy and lighting controls model.

Sensitivity Analysis

The actual sensitivity analysis was performed in the Matlab simulation environment. Code used to determine the sensitivity analysis was downloaded directly from the European Commission Joint Research Center (2011). The code was first tested against a mathematical model (Burhenne, Jacob, & Henze, 2011), which allowed detailed understanding of the structure of the code to verify the location of appropriate connections to the models being studied.

Scatterplot Analysis with All Free Parameters

The first step of the sensitivity analysis involved examining the scatterplots of the annual energy data with respect to the various free parameters using both the Reinhart and Lindelof intermediate switch-on curves. Figures Figure 25 through Figure 34 present these associated scatterplots. Where heteroscedasticity was observed, a linear curve fit was applied, and the resultant equation and coefficient-of-determination R^2 value are reported. Figure 35 illustrates the relative frequency of annual energy density, one for each data set using the Reinhart and Lindelof curves.
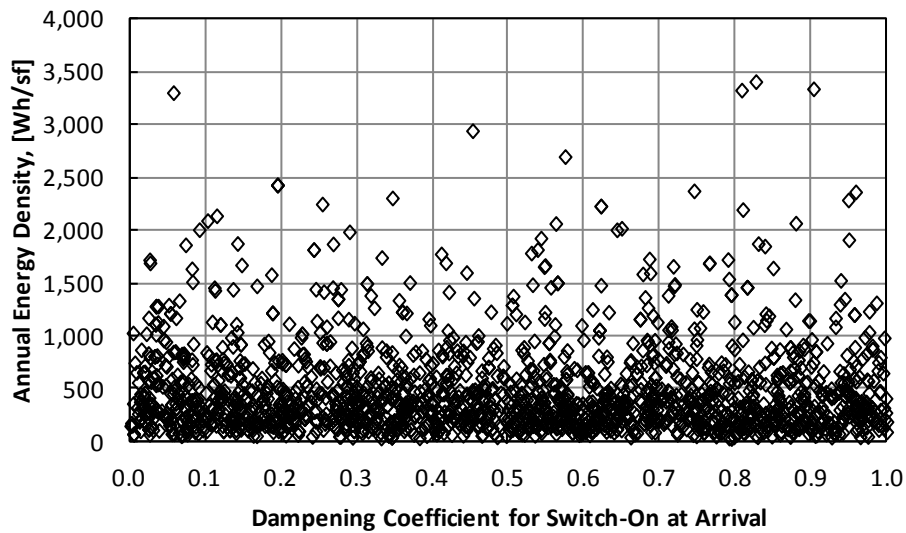
Figure 25: Scatterplot of annual energy density as a function of the dampening coefficient for switch-on at arrival assuming the Reinhart intermediate switch-on function.
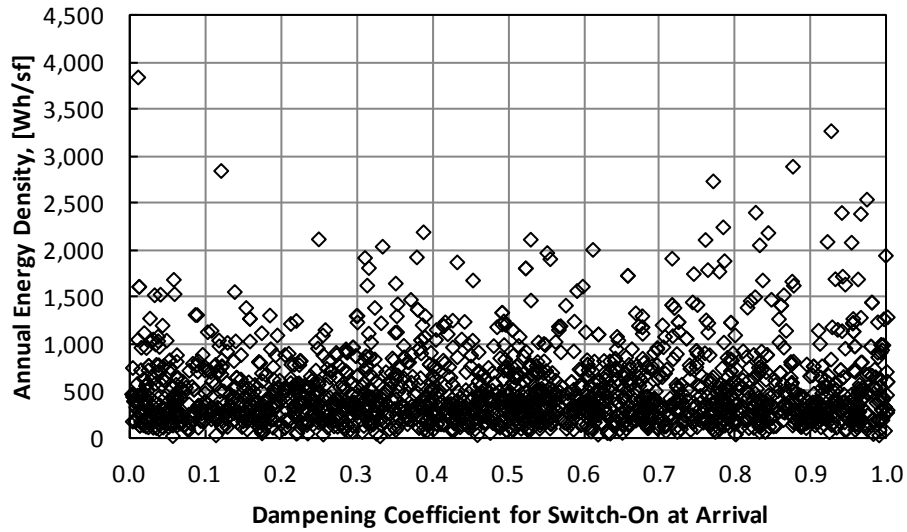
Figure 26: Scatterplot of annual energy density as a function of the dampening coefficient for switch-on at arrival assuming the Lindelof intermediate switch-on function.
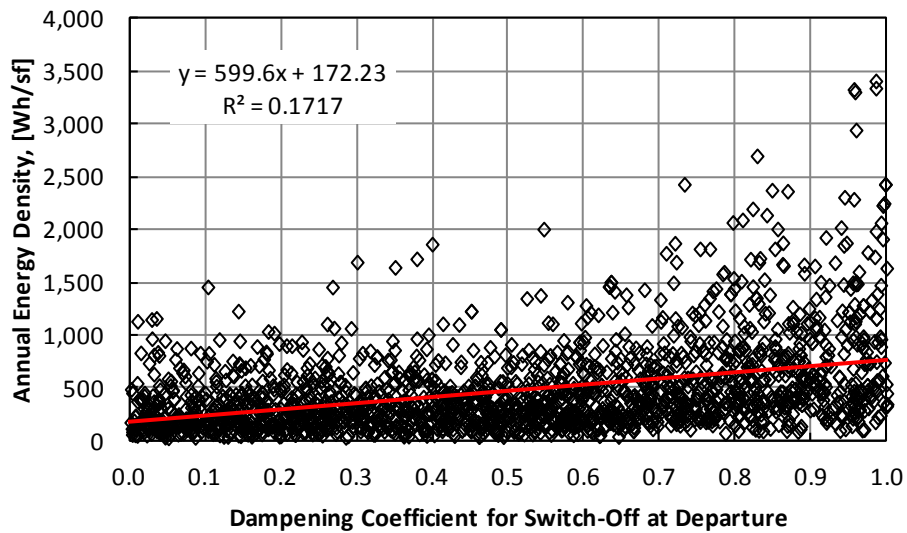
Figure 27: Scatterplot of annual energy density as a function of the dampening coefficient for switch-off at departure assuming the Reinhart intermediate switch-on function.
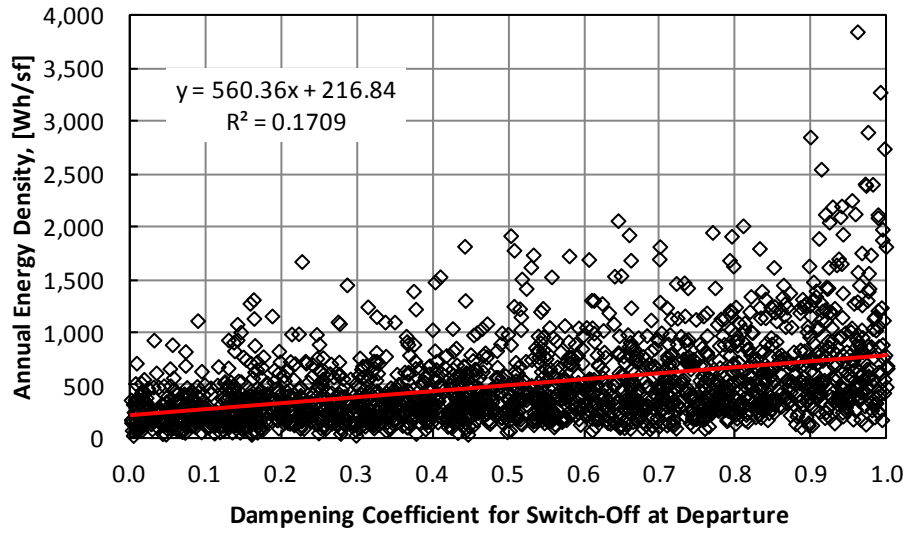
Figure 28: Scatterplot of annual energy density as a function of the dampening coefficient for switch-off at departure assuming the Lindelof intermediate switch-on function.
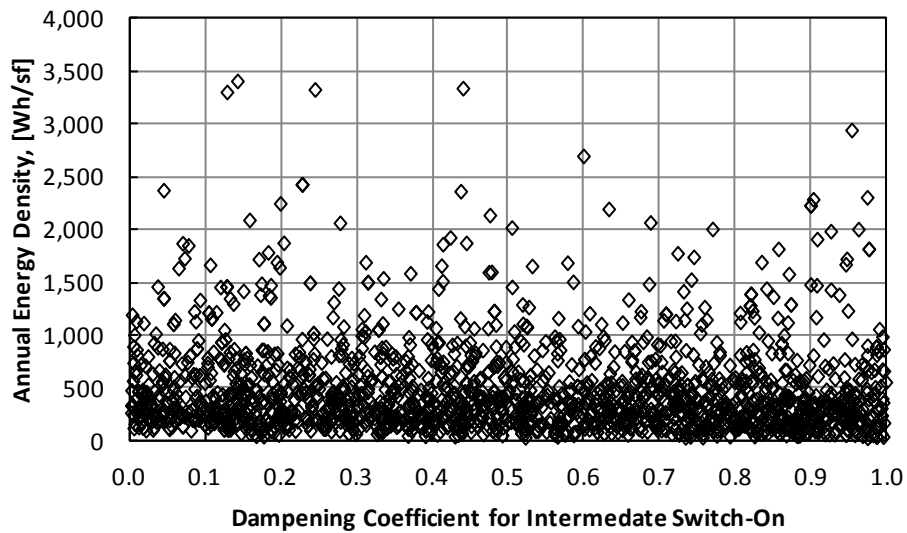
Figure 29: Scatterplot of annual energy density as a function of the dampening coefficient for intermediate switch-on assuming the Reinhart intermediate switch-on function.
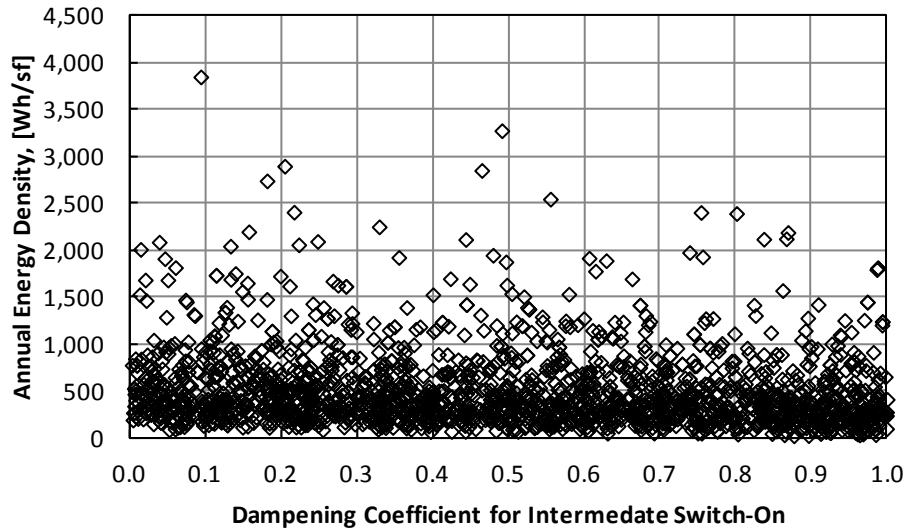
Figure 30: Scatterplot of annual energy density as a function of the dampening coefficient for intermediate switch-on assuming the Lindelof intermediate switch-on function.

$$y = 545.45x + 200.09$$
$$R^2 = 0.1407$$
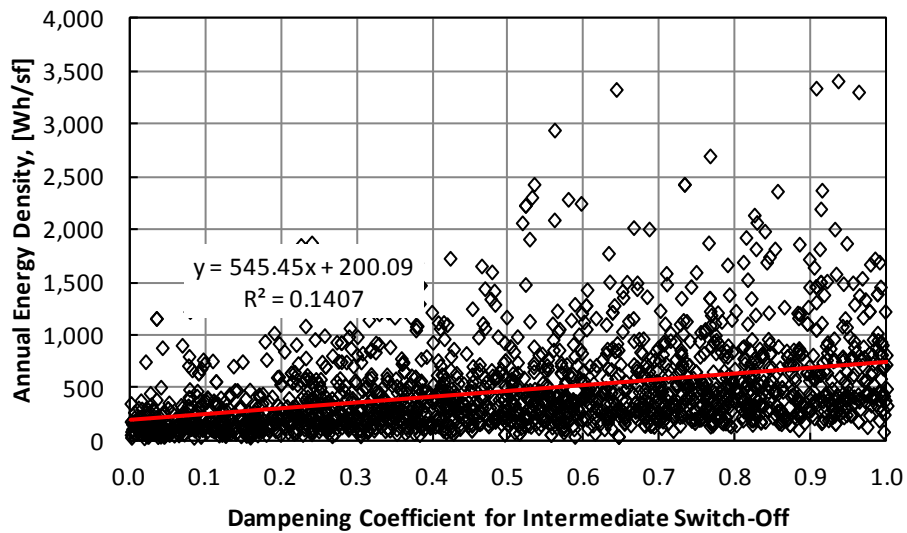
Figure 31: Scatterplot of annual energy density as a function of the dampening coefficient for intermediate switch-off assuming the Reinhart intermediate switch-on function.
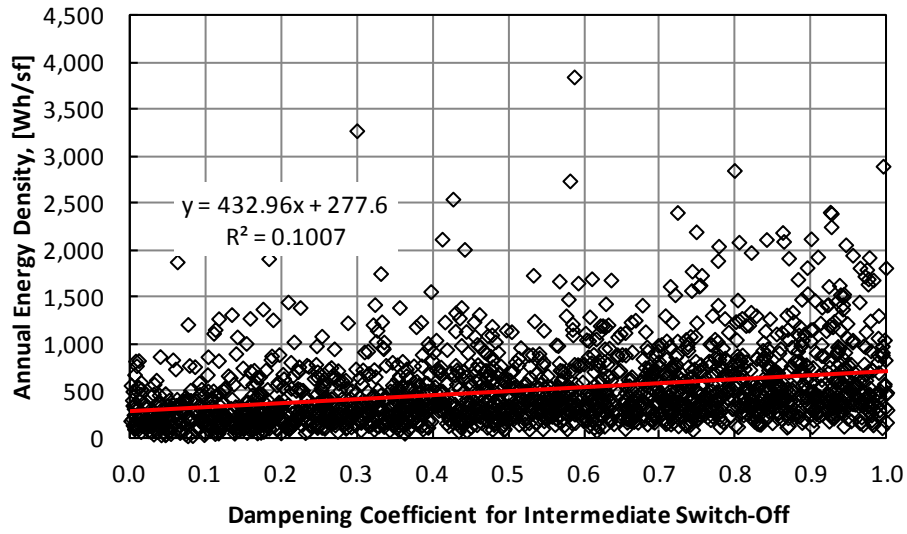
Figure 32: Scatterplot of annual energy density as a function of the dampening coefficient for intermediate switch-off assuming the Lindelof intermediate switch-on function.
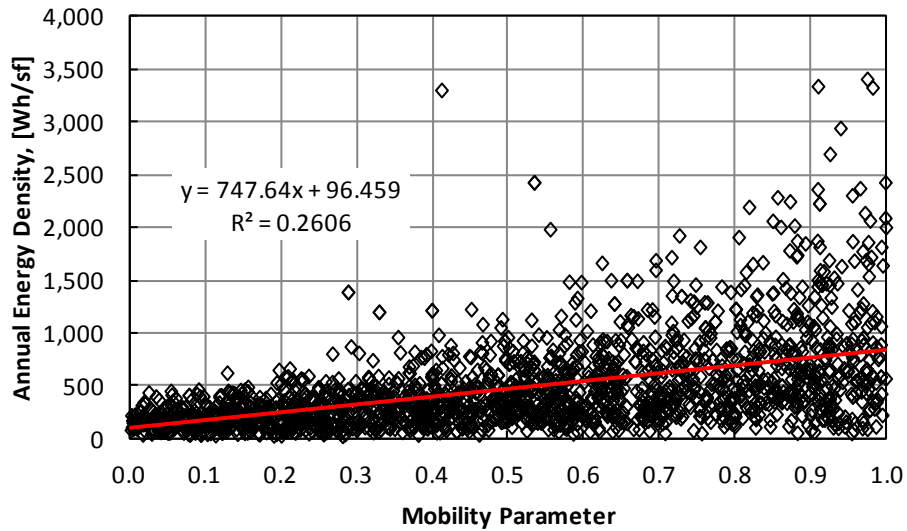
Figure 33: Scatterplot of annual energy density as a function of the mobility parameter assuming the Reinhart intermediate switch-on function.
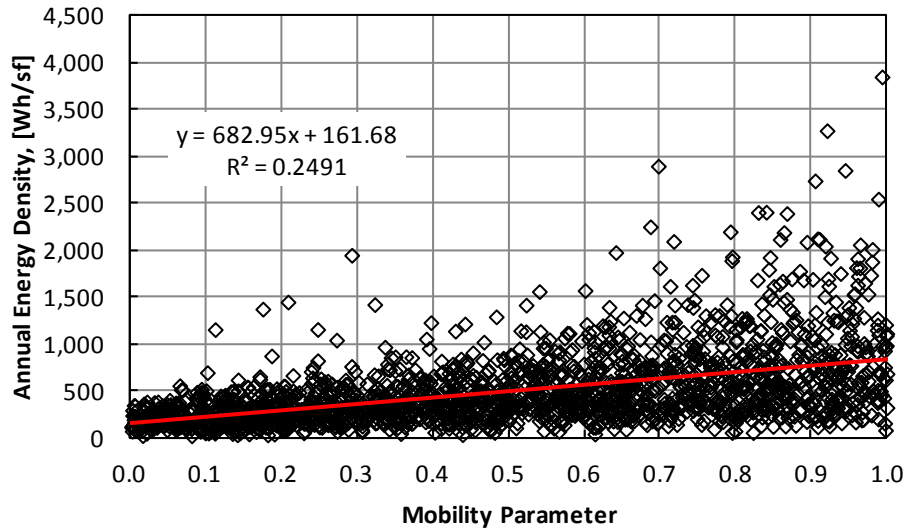
Figure 34: Scatterplot of annual energy density as a function of the mobility parameter assuming the Reinhart intermediate switch-on function.
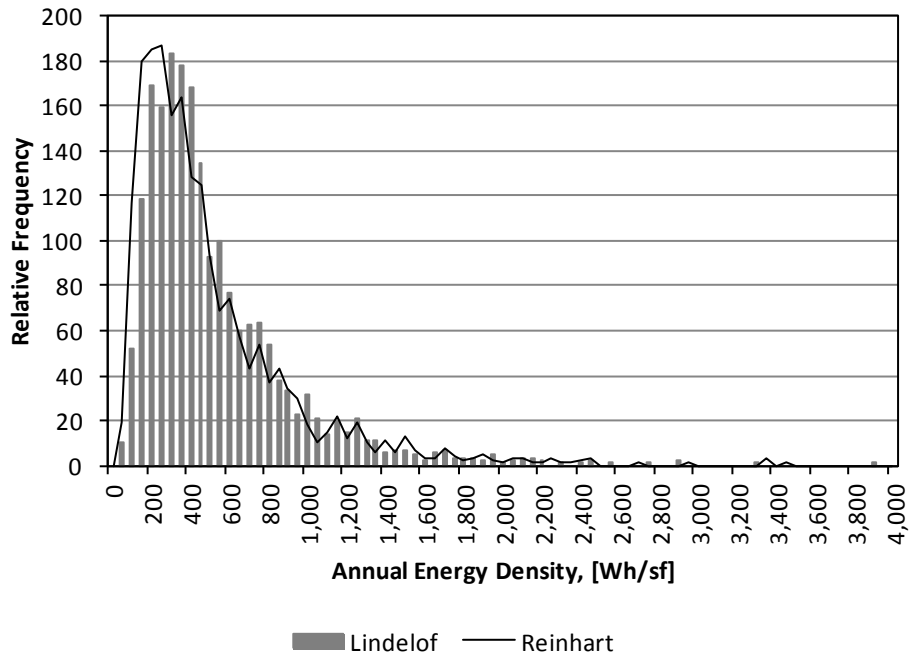
Figure 35: Relative frequency of annual energy density results comparing Reinhart and Lindelof intermediate switch-on action curves.

In general, it was found that little difference was exhibited in the scatterplots for each variable when considering the Reinhart vs. the Lindelof intermediate action curves. This is likely due to the overall low action probabilities across the intermediate switch-on curves, and thus low impact of the intermediate switch-on action on the overall energy results.

Additionally, no general trend was observed for any of the examined variables. The scatterplots all show a tendency toward low energy density, and this is due to the skew observable in the relative frequency plot.

Sensitivity Analysis with All Free Parameters

This first analysis included five free parameters: the mobility parameter, and the dampening coefficients applied to all four lighting action probabilities (switch-on at arrival, intermediate switch-on, intermediate switch-off and switch-off at departure). Additionally, the analysis was performed using both the original intermediate switch-on probability curve defined by Reinhart & Voss (2003) and included in the original Lightswitch-2002 algorithm, and the recommended intermediate switch-on probability data defined by Lindelof & Nicolas (2006).

Table 5 provides the results of this analysis, showing the sensitivity index and total effect index for each free variable using both of the intermediate switch-on action curves, and based on N=2,000 simulations. As shown, the sensitivity indices, using either of the intermediate switch-on action curves, do not sum to 1, indicating that the effect of these free variables on the variance of the overall model is not simply additive, but that the variables interact to contribute to overall model variance. Using the Reinhart curve, the sensitivity indices sum to 0.570, and using the Lindelof curve, sum to 0.600, indicating that the selection of the intermediate switch-on action curve has little influence on the additivity of the model variance.

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Table 5: Results of sensitivity analysis with all free parameters.

		Dampening Coefficients				Mobility Parameter
		On	Off	Intermediate On	Intermediate Off	
Reinhart	Si	0.006	0.185	0.014	0.104	0.261
	St	0.417	1.079	0.424	0.790	1.211
Lindelof	Si	0.006	0.199	0.013	0.110	0.272
	St	0.461	1.057	0.503	0.802	1.134

Figure 36 illustrates normalized total effects when using the Reinhart intermediate switch-on action curve and Figure 37 illustrates the same assuming the Lindelof curve. These values were determined by evaluating the contribution of the total effect index of each free variable to the sum of the five total effect indices. As shown, the mobility parameter is the largest contributor to the overall model variance when considering both intermediate switch-on action curves. Intuitively this aligns with the idea that the largest variance in energy consumption will be due to variations in occupancy patterns, and not necessarily to lighting actions.
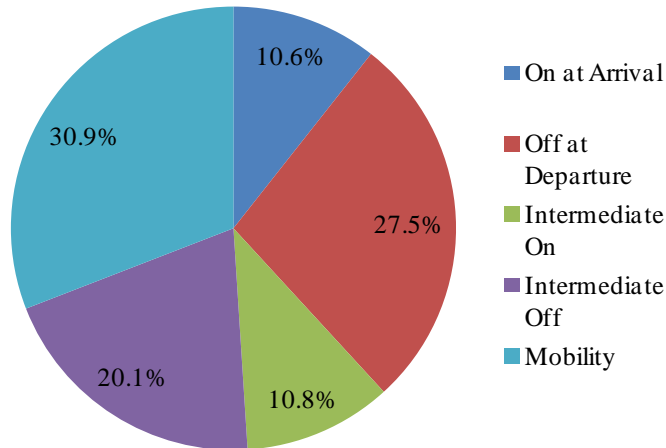
Figure 36: Variance of total model combination due to each dampening coefficient assuming the Rienhart intermediate switch-on action probability.
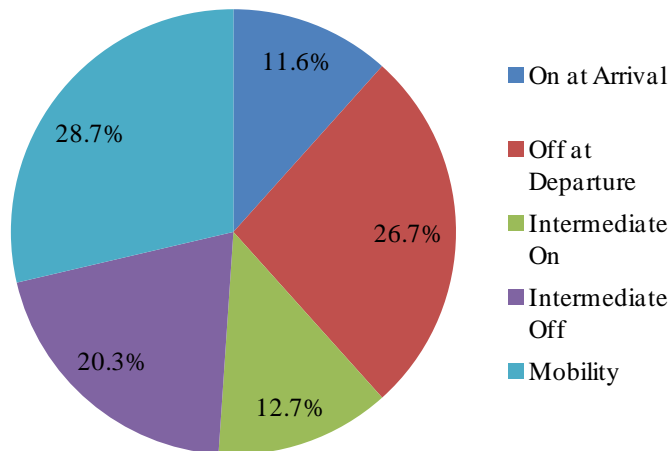
Figure 37: Variance of total model combination due to each dampening coefficient assuming the Lindelof intermediate switch-on action probability.

In both cases, the impact of the switch-off at departure action accounts for the next largest variability in the final model results. This again follows intuition in that the largest potential for wasted energy is lighting left on overnight or during weekends or longer absences. Due to the stochastic nature of the lighting action model, the switch-off at departure action can

result in widely varying lighting energy use predictions, so this particular action curve should be of specific interest in future data collection efforts.

Again in both cases, the intermediate switch-off action represents the third highest contributor to the overall model variance.

The intermediate switch-on action represents the fourth highest contributor to overall model variance in both cases. Essentially, the exact shape of the intermediate switch-on action curve, whether by Reinhart or Lindelof, has little influence on the overall model variance. This is surprising considering the vastly different shapes of those two action curves, though both represent very low action probabilities even at their highest.

The smallest contribution in both cases is the impact of switch-on at arrival. This is fairly surprising considering that the impact of intermediate switching actions is directly impacted by the initial switch-on action. However, with the particular occupancy pattern generated by the occupancy model paired with the particular daylight availability simulated, arrivals typically happen early in the day, before the available daylight has reached a level sufficient to significantly diminish the likelihood of a switch-on action.

The pattern that emerges here is that the impact of the probability of any switch-off action, be that at departure or during occupied periods, contributes most significantly to the overall model variance. The impact of the switch-on actions combine to 21.4% of the model variance assuming Reinhart and 24.3% of the model variance assuming Lindelof. In either case, that combination is less than the impact of the switch-off at departure alone.

Sensitivity Analysis with Limited Free Parameters

The next phase of the sensitivity analysis involved controlling the mobility parameter μ to assess only the impact of the various switching actions. The Lindelof intermediate switch-on

action was used for all six data sets. For this analysis, the mobility parameter was fixed at six

possible values. The six values chosen were as follows:

- 0: This is the minimum singular value included in the algorithm author's data set.

- 0.028: This is the minimum average weekly value included in the algorithm author's

  data.

- 0.040: This is the average mobility parameter when considering the value at each time

  step over all twenty weeks of data included in the algorithm author's data.

- 0.065: This is the maximum average weekly value included in the algorithm author's data

  set.

- 0.667: This is the maximum singular value included in the algorithm author's data set.

- 1: This is the maximum theoretical value.

Figures Figure 38 through Figure 43 illustrate the determined relative total effect indices for

these six settings. Figure 44 compares the results of all six simulations.

Table 6: Results of first-order sensitivity analysis with mobility parameter fixed.

Mu	Si			
	On at Arrival	Intermediate Off	Intermediate On	Off at Departure
0	0.0307	0.4294	0.0967	0.1026
0.028	0.0124	0.3585	0.1014	0.1263
0.040	0.0072	0.3411	0.1076	0.1558
0.065	0.0145	0.3752	0.1019	0.1732
0.667	0.0378	0.2087	0.0559	0.4757
1	0.0024	0.1285	0.0351	0.5003

Table 7: Results of total sensitivity analysis with mobility parameter fixed.

Mu	St			
	On at Arrival	**Intermediate Off**	**Intermediate On**	**Off at Departure**
0	0.5310	1.8087	1.0459	0.9331
0.028	0.4954	1.4545	0.8166	0.9882
0.040	0.4325	1.3789	0.7520	1.0459
0.065	0.4709	1.5724	0.7428	1.1434
0.667	0.5748	1.0905	0.5924	1.5900
1	0.5618	1.0928	0.5487	1.7935
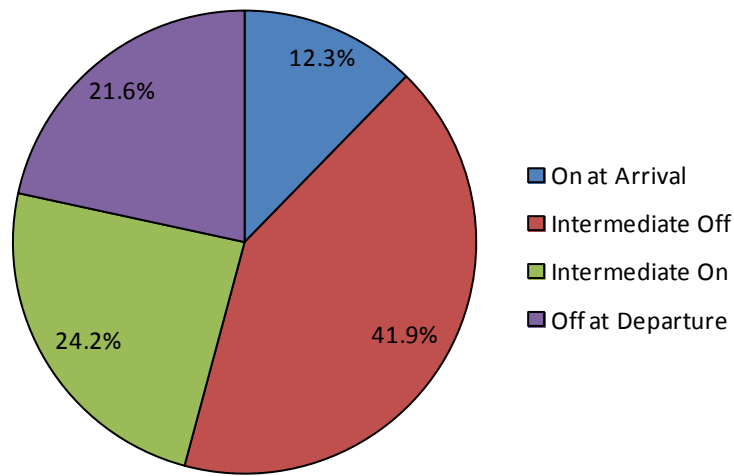
Figure 38: Variance of total model combination due to each lighting action dampening coefficient assuming mu = 0.
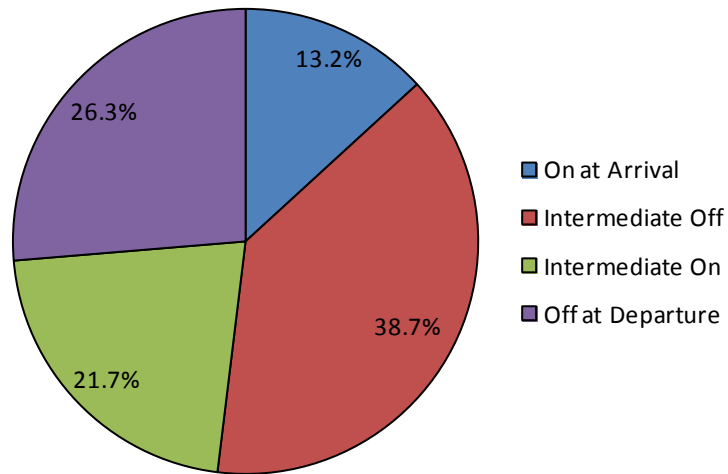
Figure 39: Variance of total model combination due to each lighting action dampening coefficient assuming mu = 0.028.
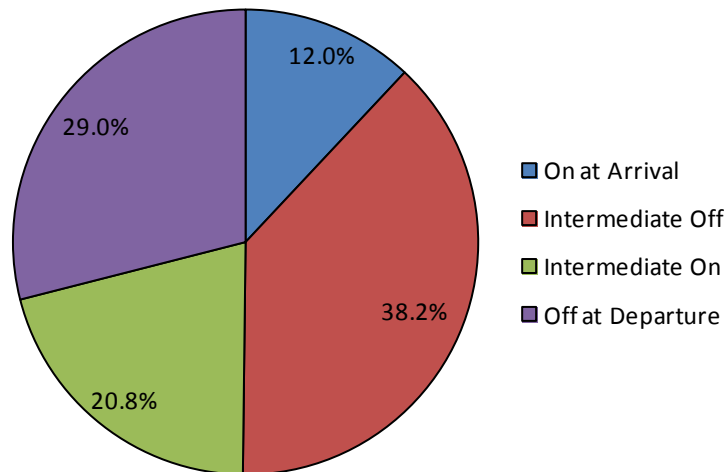
Figure 40: Variance of total model combination due to each lighting action dampening coefficient assuming mu = 0.040.
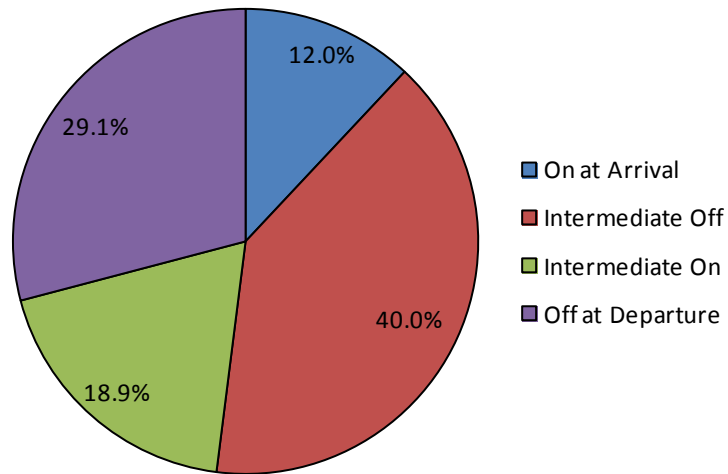
Figure 41: Variance of total model combination due to each lighting action dampening coefficient assuming mu = 0.065.
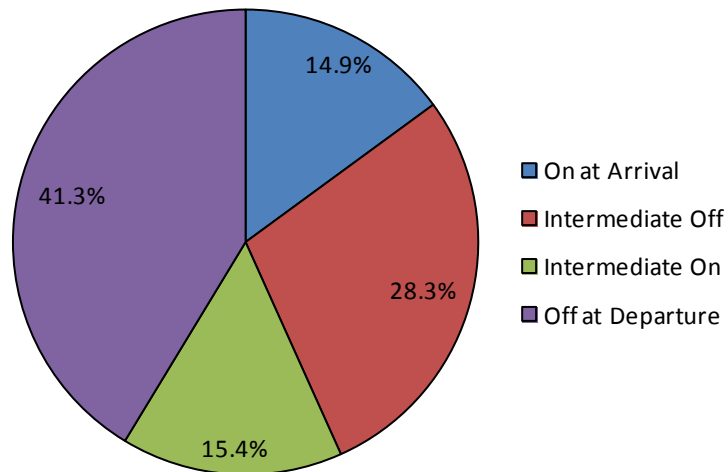
Figure 42: Variance of total model combination due to each lighting action dampening coefficient assuming mu = 0.667.
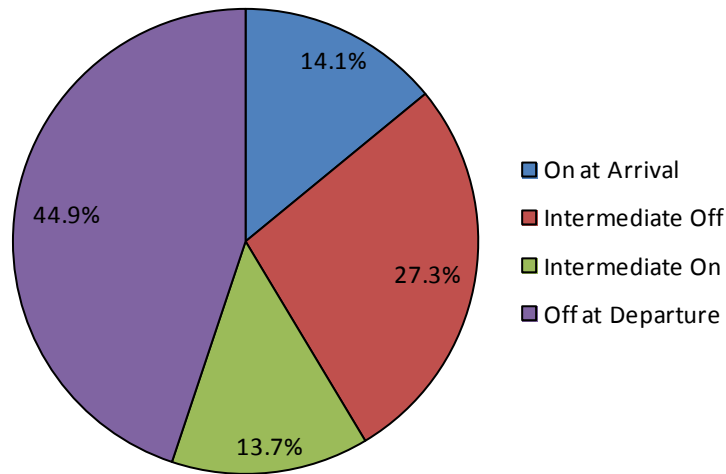
Figure 43: Variance of total model combination due to each lighting action dampening coefficient assuming mu = 1.
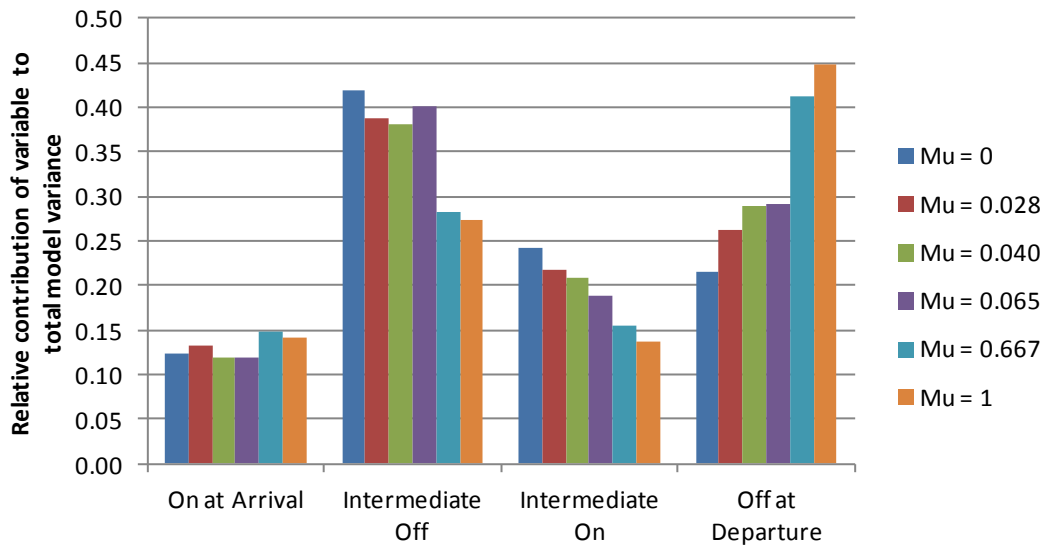
Figure 44: Comparing the impact of the fixed mobility parameter on the relative contribution to the total model variance.

As shown in all seven figures, the impact of the switch-on at arrival action on the variance of the overall model is the smallest, and is also fairly uniform independent of the mobility parameter.

The intermediate switch-on action generally is the next lowest contributor to model variance. The pattern noted in Figure 44 for this parameter is also very interesting, illustrating a decreasing contribution with increasing mobility parameter. This can be interpreted as increased mobility reduces the amount of extended periods of occupancy, thus reducing the amount of time when an intermediate action can actually occur.

The off switching actions, both intermediate and at departure, are generally the highest contributors to the overall model variance. It is interesting to note an inverse relationship between these two parameters: in general, as the mobility of the occupant increases, the impact of the intermediate switch-off action is reduced and the impact of the switch-off at departure action is increased. Again, this can be interpreted as increased mobility reduces the amount of extended periods of occupancy, causing more frequent departures. The combination of these two allows the dominant contributor to shift from intermediate actions when mobility is low to departure actions when mobility is high. Additionally, the first four settings of mobility are rather tightly grouped at 0.065 and below, and there is then a large increase to the next sets at 0.667 and 1. This large change in mobility accounts for the large decrease in impact by the intermediate action and large increase in impact by the departure action illustrated in Figure 44.

Comparison to Deterministic Scheduling

Whole-Building Evaluation

Figure 45 illustrates the results of the whole-building simulations. For each category, the first descriptor indicates the scheduled used (Alternative Compliance Manual (ACM), DOE-2, and Business Hours) and the second descriptor indicates the basis for the lighting power density (actual installed or allowed under Standard 90.1). As shown, the deterministic full-building analysis was first performed using the actual installed lighting power density. The analysis was

also performed using the allowable lighting power density under ASHRAE/IESNA Standard 90.1, which is slightly higher than actually installed.
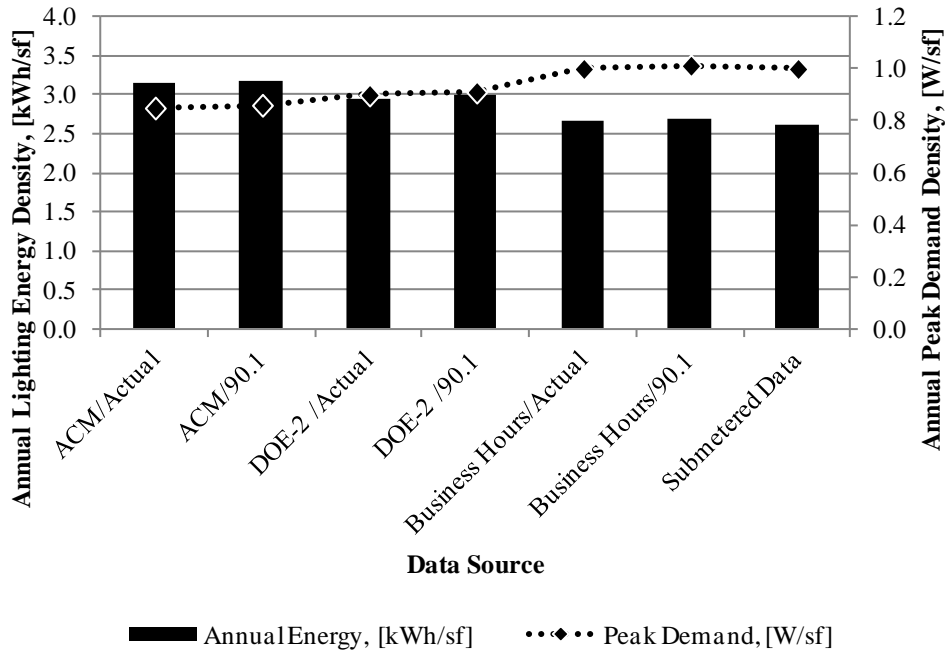
Figure 45: Comparing results of deterministic predictions of annual whole-building lighting energy use and annual peak demand to sub-metered lighting energy data.

As shown, all of the deterministic schedules overestimated the annual energy use. The Business Hours schedule, when using the actual installed lighting power density, resulted in the estimation that fell closest to the actual sub-metered energy data. Conversely, the ACM and DOE-2 schedules both underestimated peak annual demand, while the Business Hours schedule was much more accurate.

When examining the results of the whole-building simulations, it was interesting to note that the NREL and DOE-2 lighting use schedules, which would be assumed to be more accurate than the Business Hours use schedule, resulted in an overestimation of the energy density and an underestimation of the peak demand density. These profiles, though, were created based on aggregate building performance, so the Business Hours profile, which is specifically tuned to this

building, was more likely to match the building performance more closely. Additionally, the

ACM profile used is simply for commercial non-mall buildings, not specific to the office

building profile. However, those two profiles stand as the best available sources for estimating

performance before the building profile is known.
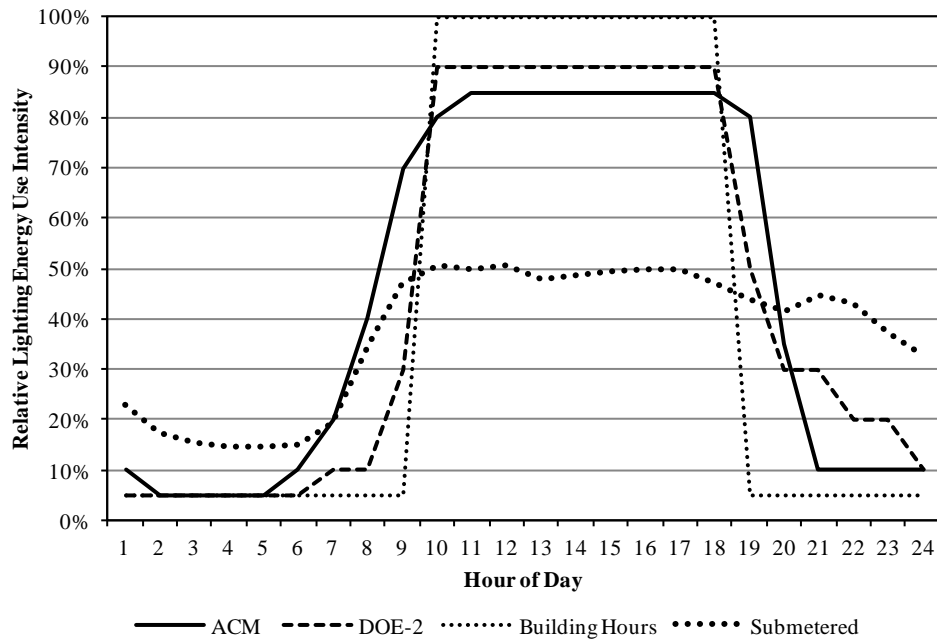
Figure 46: Comparing results of deterministic predictions of whole-building lighting energy use to sub-metered lighting energy data for a typical weekday.

The Business Hours profile assumed an "all on" scenario during the day, which allowed

the peak demand density to match the data set, where at least one "all on" event had occurred.

Figure 46 illustrates the average weekday daily profile for each simulation method and the sub-

metered data. As shown, the Business Hours profile assumes a typical higher mid-day use and

lower overnight use than was found from the sub-metered data, despite the fact that over a full

year, the annual energy prediction of the Business Hours profile matches the sub-metered data

well. Yet, from a time-dependent standpoint, the Business Hours profile is highly inaccurate.

The two remaining profiles, ACM and DOE-2, both result in an overestimation of the annual energy use and an underestimation of the peak demand. Neither of those profiles reaches full use during the day, so an "ALL ON" demand scenario would not be modeled. In aggregate, their energy predictions overestimate daytime use and slightly underestimate nighttime use when compared to this facility, leading to an overall overestimation of annual energy use.

Figure 47 illustrates the average Saturday daily profile for each simulation method and the sub-metered data, and Figure 48 shows the same for the average Sunday profile. As shown, there is a significant mismatch of profile types on these weekend days. The submetered data shows typically higher overnight consumption than peak daytime consumption, which is the opposite of the general pattern observed from the ACM and DOE-2 schedules. The reason for this is likely tied to the building hours, use types, and daylight availability, with high overnight occupancy rates on the weekends, and maximized use of daylighting during the weekend days.
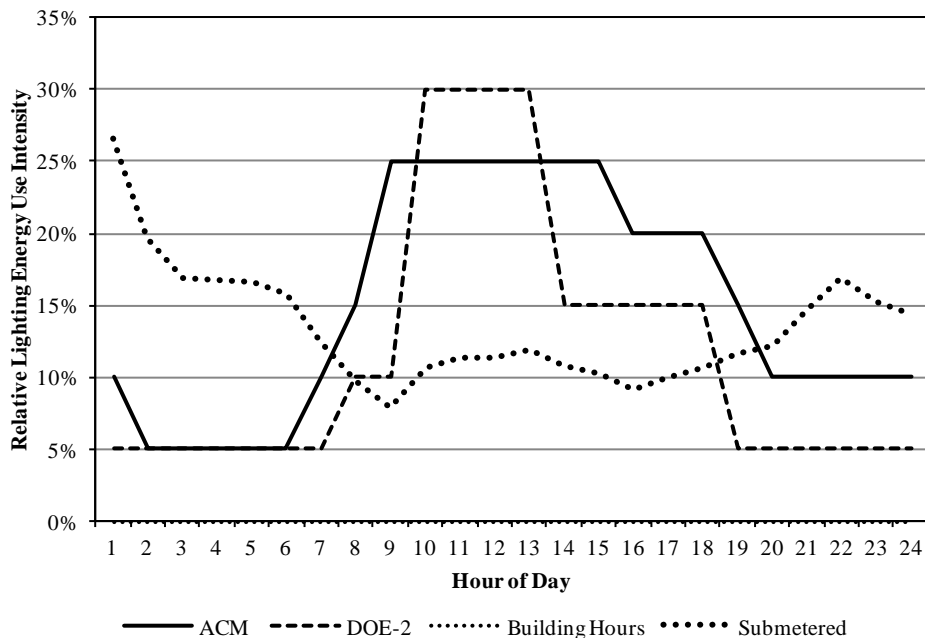
Figure 47: Comparing results of deterministic predictions of whole-building lighting energy use to sub-metered lighting energy data for a typical Saturday.
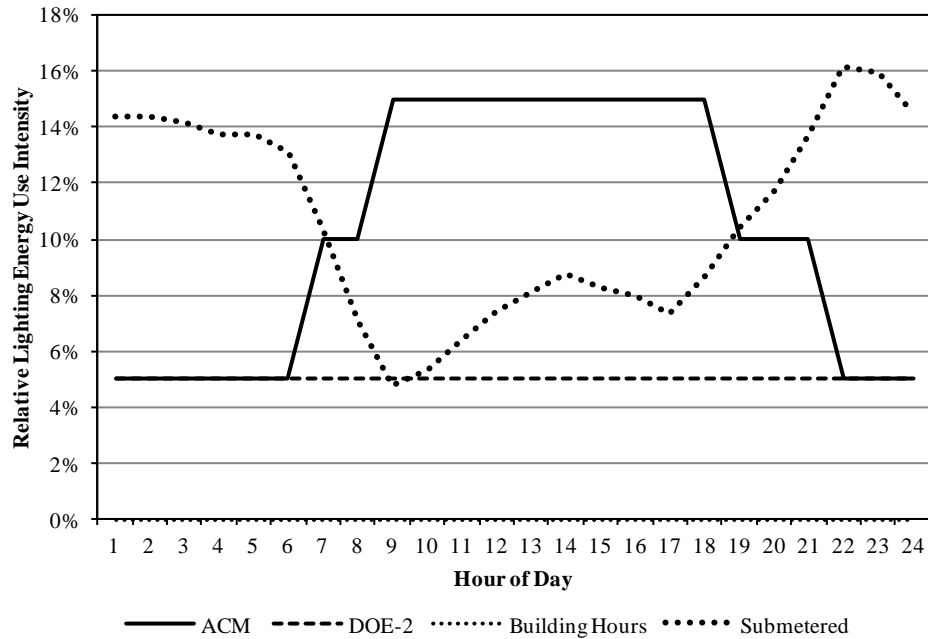
Figure 48: Comparing results of deterministic predictions of whole-building lighting energy use to sub-metered lighting energy data for a typical Sunday.

Private Office-Only Evaluation

As described previously, the annual energy use and peak demand of the private offices only was of particular interest because the advanced stochastic simulation method is currently built only for that space type. The results of the six advanced stochastic simulations were compared to the results from deterministic modeling efforts both in terms of annual energy density and annual peak demand density. Again, these results were compared to the sub-metered lighting energy data that was filtered to estimate the private office consumption, as described in the *Data Filtering* section above.

Figure 49 summarizes the results of the simulations for the private offices only. As shown, all six advanced simulations (AS1 through AS6) resulted in a much lower anticipated annual energy density than the deterministic models. Examining the predicted annual energy density alone showed that the deterministic schedule consistently resulted in higher predicted

energy density. The results of the advanced simulations still showed large variations amongst themselves due to the various distributions of user types and their subsequent interaction with the lighting controls in response to daylight conditions.
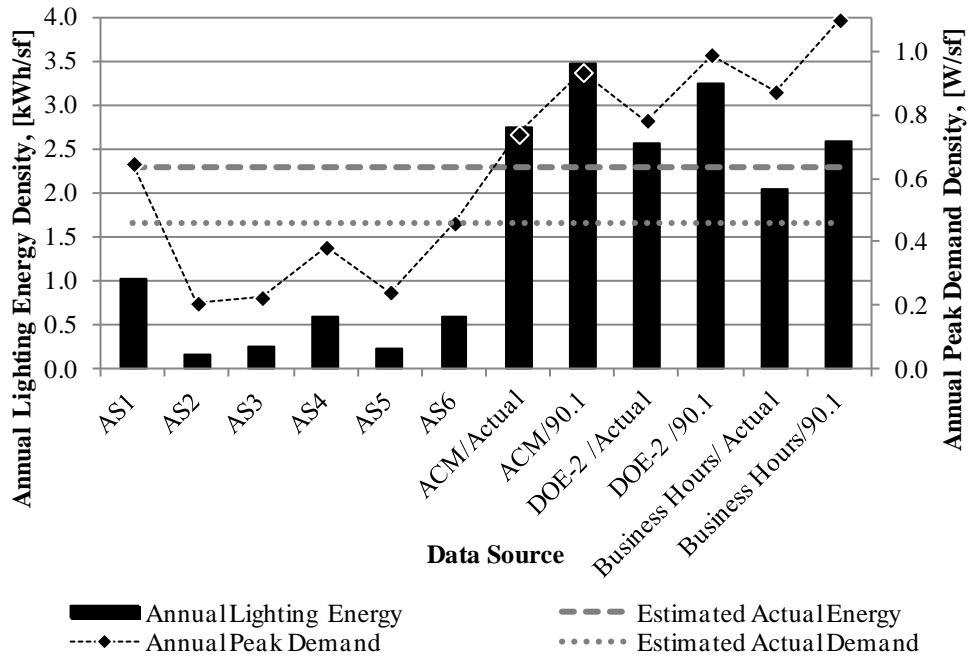
Figure 49: Comparing results of stochastic and deterministic predictions of annual private office lighting energy use and annual peak demand to sub-metered lighting energy data.

Similarly, the anticipated peak annual demand density found using the deterministic methods is consistently higher than found using the advanced simulation, though the peak demand simulated from AS1, which assumed all Passive users that essentially do not take daylight into account for their switching decisions, was similar to the lower values found using the deterministic modeling.

With the caveat that the sub-metered data was based on the whole building energy use and simply scaled, the results of these simulations were evaluated against the filtered sub-metered data. However, the estimated hourly intensity information provided in the ACM, DOE-2 and Business Hours schedules essentially do the same thing by assuming that the use profile

within the private offices can directly mimic the use profile of the entire building. That being said, the deterministic models, specifically the DOE-2 model using the actual LPD, came close to matching the filtered sub-metered data, but the deterministic models consistently overshot the estimated peak demand. Meanwhile, the peak demand density found using the settings of AS6, where all users were assumed to behave with a 75% dampening coefficient, nearly exactly matched the filtered sub-metered data.

In the private office simulations, it was shown that the use of the stochastic modeling, which includes predictions of the interaction of the occupants with the lighting control system, resulted in a much lower annual energy prediction than all of the deterministic models, which do not account for daylight-responsive occupant action, and the estimated actual use for the investigated building. Likewise, the peak annual demand was also estimated to be much lower when using the stochastic models compared to the deterministic schedules.

Specifically, of the deterministic schedules, the ACM profile resulted in the highest energy use and the Business Hours profile in the lowest. Conversely, the ACM profile resulted in the lowest predicted peak demand of the deterministic schedules, and the Business Hours in the highest. Ultimately, of the deterministic models, the lower estimated peak demand of the ACM schedule best matched the filtered sub-metered data and the Business Hours schedule resulted in the closest match of the annual energy use.

When examining the advanced simulations, it was interesting to note the variation of the six different scenarios in terms of peak demand and energy use, and their correlations to the types of users. Figure 50 illustrates the relative lighting energy use intensity for a typical weekday for each of the six advanced simulations. Intuitively, the less the users consider their daylight availability, the higher the energy use should be. This was confirmed with the model,

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where AS1 assumed all 'Passive' users, who will always switch-on lighting at arrival, will not engage in intermediate switching actions, and who are equally likely to switch-off the lighting at departure. Conversely, intuition leads one to believe that the more 'Active' the users are, the more they consider their daylight and make adjustments to their lighting throughout the day to respond to daylight, then the lower their lighting energy use will be. This was also confirmed with the model, where AS2 assumed all 'Active' users.
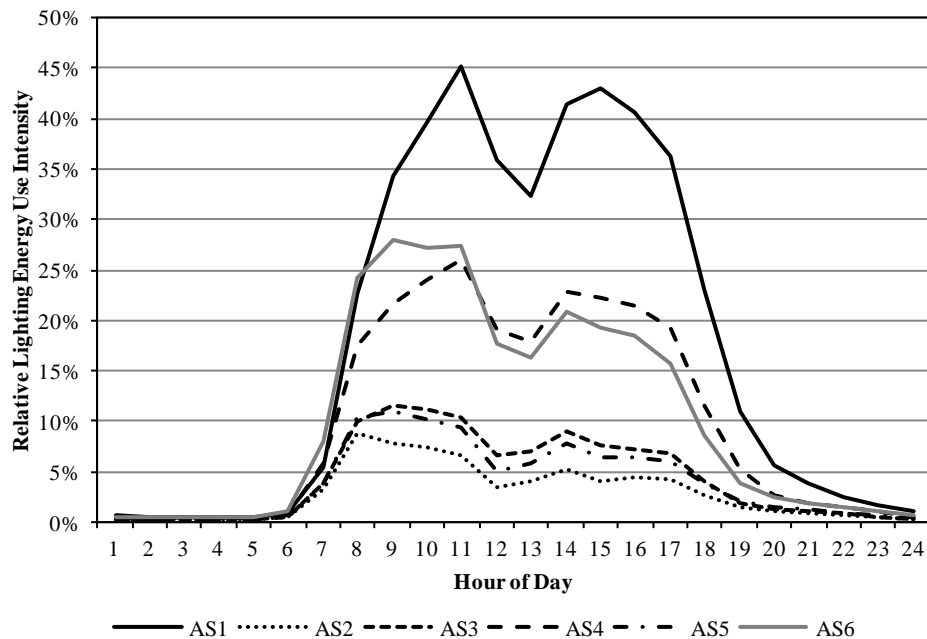
Figure 50: Comparing results of six different settings for stochastic predictions of private office lighting energy use.

The intermediate models provide insight into how the different user types can be modeled and how that modeling impacts the projected energy use. After AS1, the next highest energy use predictions came from AS6, which assumed that all of the users acted with a dampening coefficient of 0.75, and AS4, which assumed a 50/50 split of 'Active' and 'Passive' users. AS6 which can be interpreted as a group of users that were less aware of or responsive to their daylighting, but more likely to respond than a true 'Passive' user, all essentially equally

contributed to the high energy use. AS4, which can be interpreted as two distinct populations of 'Active' and 'Passive' users, showed savings over AS1 from the inclusion of 'Active' users, but the significantly higher energy consumption of the 'Passive' users served to essentially negate much of the savings achieved by the 'Active' users. AS3 then followed, which assumed all users behaved midway between an 'Active' and a 'Passive' user. AS5, which assumed all users behaved with a dampening coefficient of 0.25, provided the next lowest annual energy use, which is due to the near-'Active' behavior of those occupants.

It is interesting to note that assuming all users behaved midway between 'Active' and 'Passive' (AS3) and assuming an equal split of 'Active' and 'Passive' users (AS4) did not result in the same energy prediction. A user midway between those two archetypes, essentially, does not result in the same energy use prediction as the mean of an 'Active' and 'Passive' user.

It is also interesting to note that the two simulations that resulted in nearly identical aggregate predictions, AS4 and AS6, show an interesting time-dependent behavior. AS6 predicts higher energy use in the morning, while AS4 predicts higher energy use in the afternoon. The high use in the afternoon of the AS4 simulation is likely due to the inclusion of pure 'Passive' users, who will activate their lighting after lunch regardless of the daylighting condition. The users in AS6, which operated with 75% dampening coefficients, were less likely to activate their lighting when returning from lunch due to the high mid-day illuminance levels. Even at the significantly reduced switching potential caused by the 75% dampening coefficient, the impact of the daylight levels led to reduced daytime energy use.

Additionally, the predicted annual energy density using this stochastic simulation method consistently resulted in energy density predictions much lower than the deterministic scheduling method, even when considering all 'Passive' users who effectively did not react to the available

daylight. This is due to the stochastic occupancy prediction that accounts for variation of user behavior instead of assuming full-day occupancy as the deterministic schedules do. Even though the 'Passive' user will employ the lighting whenever the space is occupied, the stochastic occupancy simulation reduces the total occupied hours, which effectively reduces the maximum lighting energy density.

Initial Validation

An initial validation effort was performed using the combined occupancy and modified lighting controls models as described previously. The daylighting model used for the initial validation effort is also the two-sky model, as described in the section titled "Daylighting Calculation Assumption Exploration" below.

Total Annual Lighting Energy Use

The first goal of the initial validation was to attempt to match the annual energy use as determined from the filtered sub-metered lighting energy data. This validation was achieved by manually tuning the five free parameters, the four dampening coefficients and the mobility parameter, where a single mobility parameter was applied to all offices together but each office had the ability to have unique dampening coefficients. Thirty-three setting combinations were examined and evaluated to determine which combination resulted in the closest energy prediction.

Figure 51 illustrates the total annual lighting energy consumed per day, comparing the results of the sub-metered data to the results of the advanced stochastic simulation. This information is also presented in Table 8.
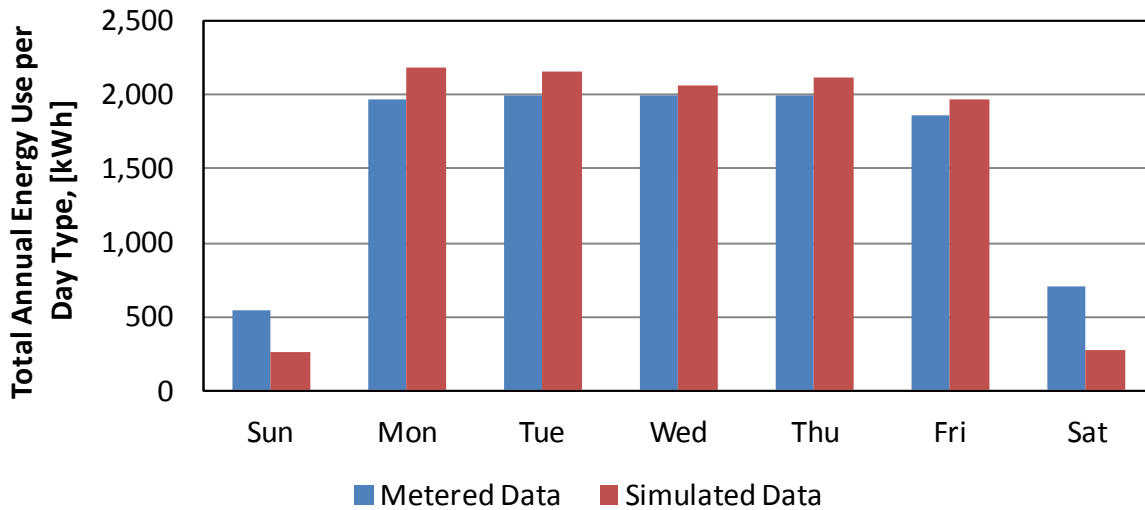
Figure 51: Annual lighting energy prediction compared to sub-metered lighting energy data for each day type.

Table 8: Results of validation analysis when attempting to match total annual lighting energy use.

	Total Annual Energy Use per Day Type							Total Annual Energy Use
	Sun	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Simulated	255	2,184	2,159	2,060	2,123	1,967	276	11,024
Difference	52.5%	11.1%	8.0%	3.1%	6.5%	5.8%	60.7%	0.3%

As shown, tuning the various free parameters allowed the model to be adjusted to fairly well match the total annual energy use prediction, with a difference of only 0.3%, or 28 kWh. When examining the day types, the weekdays typically resulted in a closer match between the sub-metered and simulated annual energy use than the weekends. The percentage difference is significant for both weekend days, but exacerbated due to the generally low energy use. One interesting anecdotal observation is that both the simulated energy use, which is based on actual metered occupancy data, and the sub-metered lighting energy data use have lower energy

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consumption on Fridays than on the other four days of the typical work week. Table 9 describes

the input parameters that were used to find this approximate match.

Table 9: Parameters for validation analysis when matching annual energy use (Set 13).

Input Variable	Values and Notes
Number of Private Offices	74
Orientation	50% South-Facing, 50% North-Facing
Lighting Control System	Bilevel: 50% Auto-On/Auto-Off, 50% Manual-On/Auto Off, 15-minute time delay
Lighting Power Density	0.87 W/sf
Blinds	Fully manual black-out
Intermediate Switch-On Curve	Lindelof
Dampening Coefficient: Switch-On at Arrival	43 offices @ 0.98, 31 @ 0, split evenly between North and South facing
Dampening Coefficient: Switch-Off at Departure	All offices @ 0
Dampening Coefficient: Intermediate Switch-On	43 offices @ 0.99, 31 @ 0, split evenly between North and South facing
Dampening Coefficient: Intermediate Switch-Off	43 offices @ 0.92, 31 @ 0, split evenly between North and South facing
Mobility Parameter	All offices @ 0.9

However, despite the close match to the annual energy use, the typical daily profiles that

resulted this annual energy use do not follow the same pattern as the sub-metered, as shown in

Figures Figure 52 through Figure 54, which present the typical lighting energy use intensity

profiles as a percentage of the installed lighting power "on" per hour for the typical weekday,

Saturday and Sunday.   The values shown on the figures indicate the peak daytime power.
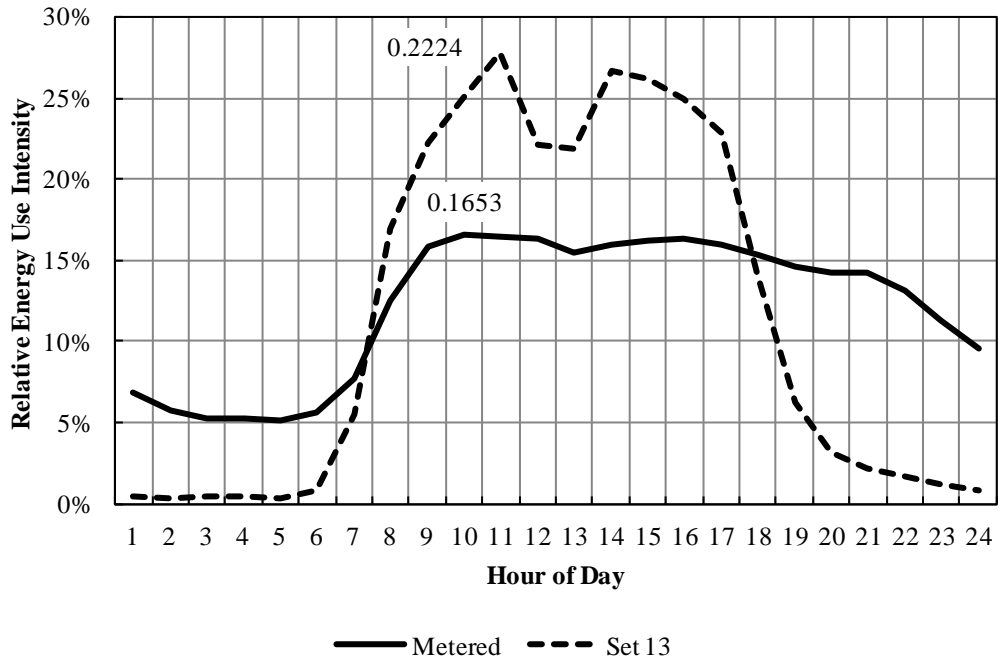
Figure 52: Results of initial validation for weekdays when matching annual energy use.
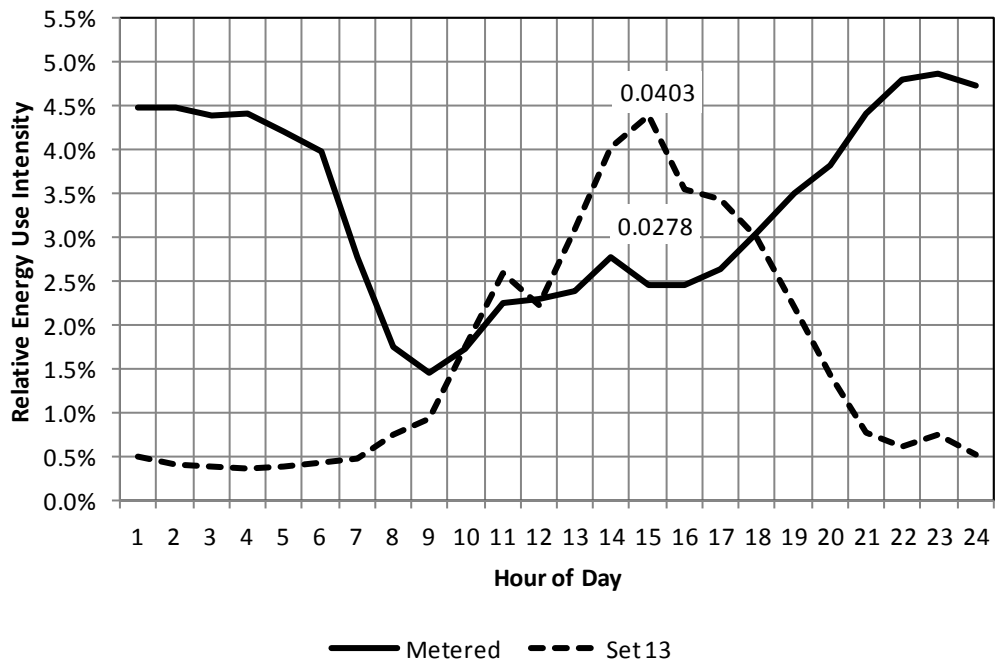
Figure 53: Results of initial validation for Saturdays when matching annual energy use.
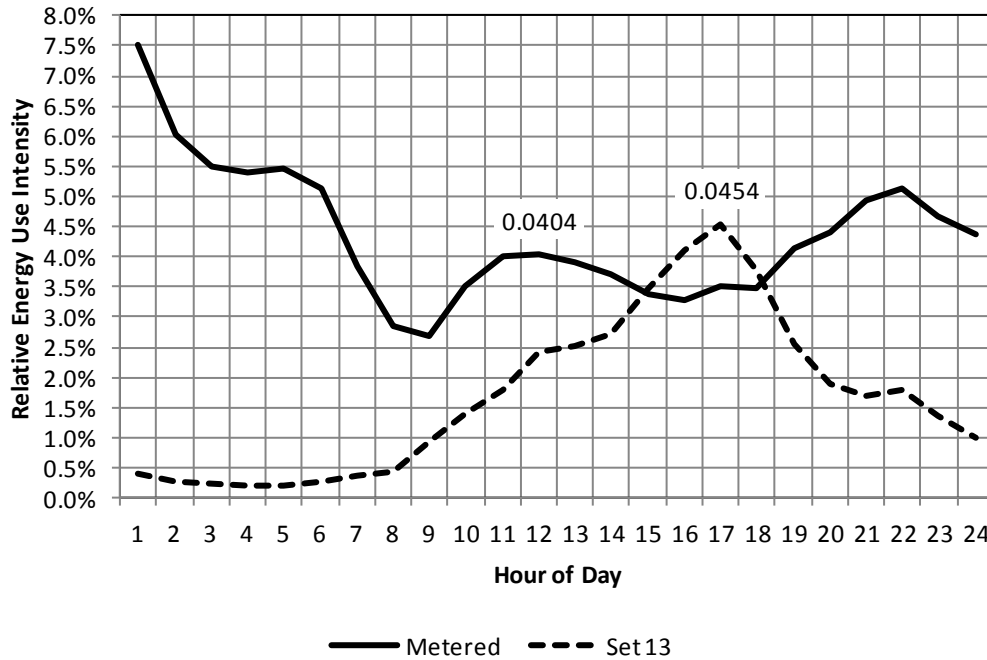
Figure 54: Results of initial validation for Sundays when matching annual energy use.

As shown, the daily profiles do not align well with that of the sub-metered lighting energy data. For the typical weekday, while the integrated energy use in similar, the shape of the simulated curve is such that peak daytime demand is significantly higher, nearly doubled, that found in the lighting energy data based on the described filtering process. The nighttime use according to the sub-metered lighting energy data is significantly higher than predicted from the modeled prediction.

For Saturdays, the overnight use as found in the data is more than eight times that predicted using the models. The predicted use drops during the daytime, as was shown during the comparison to the deterministic modeling results. For Sundays, the observed pattern is very similar to that seen on Saturdays, indicating continued occupancy during these times.

Matching Daily Profiles

Since a major goal of this effort was to explore tools to predict lighting energy use and peak demand, and the first attempt at validation illustrated a large mismatch when predicting peak demand, a second set of initial models were created to assess the parameters necessary to approximate the peak daily demand. Three different parameter sets were necessary to model each day type, one each to model Weekdays, Saturdays and Sundays, since the original error was very different on those days.
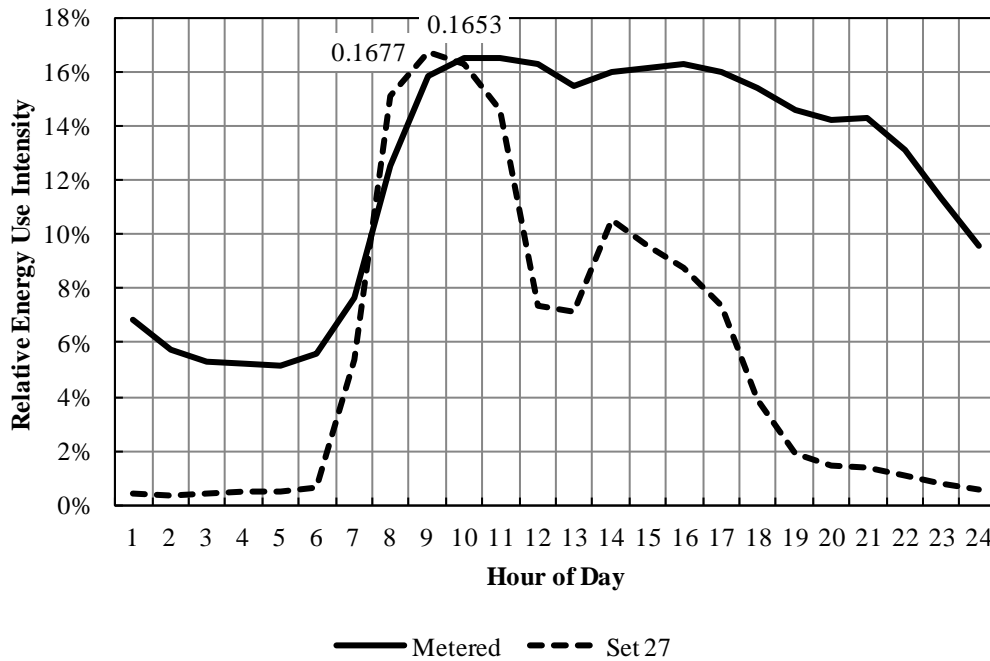
Figure 55: Results of initial validation for weekday when matching peak demand.

Figure 55 illustrates the results of the model set that allowed the closest match of the typical day peak demand. Table 10 shows the parameter settings used to achieve this near match. As shown, to reduce the daily energy consumption to allow the predicted typical daily peak energy use to match that of the sub-metered data, first the mobility parameter was decreased to reduce the number of entering events and thus the opportunities for a switch-on,

since the intermediate action probabilities are much lower than the probability of switch-on at arrival across illuminance levels. Next, the dampening coefficients for both switch-on actions, at arrival and intermediate, were adjusted downward to reduce the amount of lighting being activated at any tie. Finally, the intermediate switch-off dampening coefficient was adjusted downward to attempt to smooth out the morning/afternoon energy difference. However, because the base occupancy model exhibited such a large dip at lunchtime, even with the dampening coefficient applied to the probability of switch-on at arrival, much less lighting is activated after lunch time. However, the predicted lighting energy use continued to follow an undesirable pattern that is inextricably linked to the occupancy model itself.

Table 10: Parameters for validation analysis when matching peak daily demand (Set 27).

Input Variable	Values and Notes
Number of Private Offices	74
Orientation	50% South-Facing, 50% North-Facing
Lighting Control System	Bilevel: 50% Auto-On/Auto-Off, 50% Manual-On/Auto Off, 15-minute time delay
Lighting Power Density	0.87 W/sf
Blinds	Fully manual black-out
Intermediate Switch-On Curve	Lindelof
Dampening Coefficient: Switch-On at Arrival	37 offices @ 0.64, 37 @ 0, split evenly between North and South facing
Dampening Coefficient: Switch-Off at Departure	All offices @ 0
Dampening Coefficient: Intermediate Switch-On	37 offices @ 0.68, 37 @ 0, split evenly between North and South facing
Dampening Coefficient: Intermediate Switch-Off	37 offices @ 0.76, 37 @ 0, split evenly between North and South facing
Mobility Parameter	All offices @ 0.04

The same process was executed for the typical Saturday lighting energy profile. Figure 56 illustrates the attempt at matching the typical Saturday peak demand, and Table 11 give the simulation parameters necessary to achieve this result.
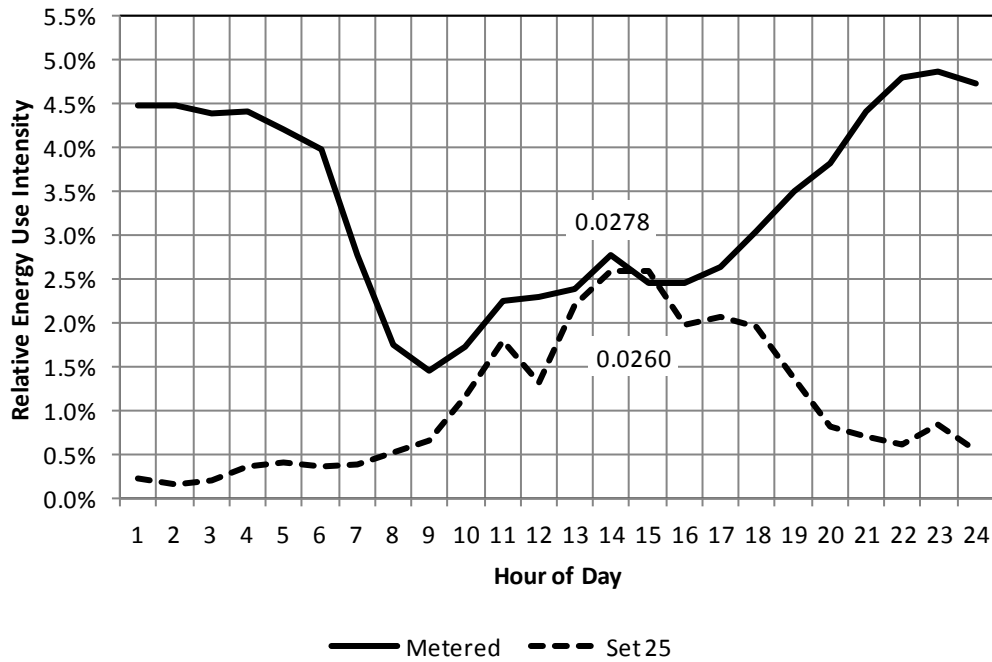
Figure 56: Results of initial validation for Saturdays when matching peak demand.

As shown, the model was adjusted to match the typical daytime peak demand. However, for the sub-metered data, the typical daily peak demand occurs overnight. Again, the shape of the predicted lighting energy curve is inextricably linked to the Page et al. (2008) occupancy model and there exist no parameters in the original algorithm to allow modifications of the occupancy pattern that would allow a prediction of lighting energy that follows even the general shape of the sub-metered data.

Table 11: Parameters for validation analysis when matching peak Saturday demand (Set 25).

Input Variable	Values and Notes
Number of Private Offices	74
Orientation	50% South-Facing, 50% North-Facing
Lighting Control System	Bilevel: 50% Auto-On/Auto-Off, 50% Manual-On/Auto Off, 15-minute time delay
Lighting Power Density	0.87 W/sf
Blinds	Fully manual black-out
Intermediate Switch-On Curve	Lindelof
Dampening Coefficient: Switch-On at Arrival	37 offices @ 0.77, 37 @ 0, split evenly between North and South facing
Dampening Coefficient: Switch-Off at Departure	All offices @ 0
Dampening Coefficient: Intermediate Switch-On	37 offices @ 0.81, 37 @ 0, split evenly between North and South facing
Dampening Coefficient: Intermediate Switch-Off	37 offices @ 0.72, 37 @ 0, split evenly between North and South facing
Mobility Parameter	All offices @ 0.04

Finally, this same process was followed for the typical Sunday lighting energy profile. Figure 57 illustrates the attempt at matching the typical Sunday peak demand, and Table 12 gives the simulation parameters necessary to achieve this result.

As shown, the peak daytime demand was very closely matched. However, similar to the Saturday analysis above, the actual peak Sunday demand occurred during the overnight hours. Using the selected occupancy and modified lighting action model, it is not feasible to achieve this nearly inverted relationship.
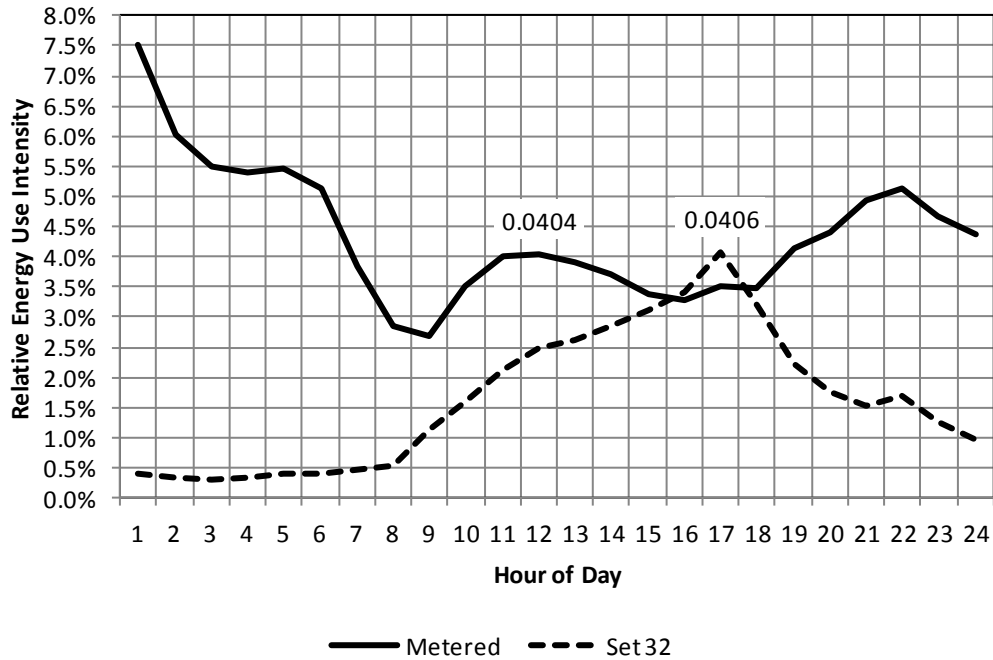
Figure 57: Results of initial validation for Sundays when matching peak demand.

Table 12: Parameters for validation analysis when matching peak Sunday demand (Set 32).

Input Variable	Values and Notes
Number of Private Offices	74
Orientation	50% South-Facing, 50% North-Facing
Lighting Control System	Bilevel: 50% Auto-On/Auto-Off, 50% Manual-On/Auto Off, 15-minute time delay
Lighting Power Density	0.87 W/sf
Blinds	Fully manual black-out
Intermediate Switch-On Curve	Lindelof
Dampening Coefficient: Switch-On at Arrival	37 offices @ 0.98, 37 @ 0, split evenly between North and South facing
Dampening Coefficient: Switch-Off at Departure	All offices @ 0
Dampening Coefficient: Intermediate Switch-On	37 offices @ 0.99, 37 @ 0, split evenly between North and South facing
Dampening Coefficient: Intermediate Switch-Off	37 offices @ 0.92, 37 @ 0, split evenly between North and South facing
Mobility Parameter	All offices @ 0.9

Conclusions from Initial Results

This overall process was intended to be used to evaluate the use of the particular

occupancy and modified lighting controls model to predict lighting energy use and peak demand,

and to understand the contribution of the various free parameters to control the simulation

results.

Conclusions from Sensitivity Analysis

As shown from the initial sensitivity analysis, the use of the Reinhart intermediate

switch-on curve or the Lindelof curve had little impact when assessing the relative contribution

of each free variable to the overall variance of the model. In both cases, the mobility parameter

was responsible for the largest portion of the total variance of the model output, when including

both first order effects and interactions. In general, this follows logic since the higher mobility

parameters cause more in-and-out actions, reducing the total amount of time the space is actually

occupied. Since the overall probabilities of actions at departure and arrival are much larger than

during intermediate occupancy, increasing mobility which leads to more in-and-out events will

overall increase the exposure to switching opportunities.

When the mobility parameter was fixed at the six predefined levels based on the author's

original data, it was shown that the dampening coefficient assigned to the probability of a switch-

on event at arrival was fairly uniform independent of the exact value of the mobility parameter.

The impact of both of the intermediate switching actions was reduced as the mobility of the

occupants increased, which again follows logically from the physical interpretation of the

mobility parameter. And finally, the impact of the dampening coefficient applied to the

probability of a switch-off action at departure was found to increase with increasing occupant

mobility. Essentially, this is tied to the increasing number of exiting events and the strong influence of the actual dampening coefficient on the probability distribution function.

Most obvious from the sensitivity analysis was the general conclusion that the occupant pattern and their likelihood to engage in switch-off actions at departure have the highest influence on the variability of the overall model results.

Conclusions from Comparison to Deterministic Predictions

The results of the deterministic model analysis also provided some interesting insight into the relationship between deterministic predictions and sub-metered data. As shown, the existing deterministic schedules in use tend to underestimate peak demand and overestimate annual lighting energy use when considering the whole building. This is likely due to the peak daytime estimates which, for the schedules presented, never reach full use. Additionally, the metered overnight use is higher than predicted through the deterministic schedules and the use patterns on the weekdays is significantly different than that presented through the deterministic schedules.

Comparing the deterministic and stochastic predictions for just the private office spaces, it was found that the predicted annual energy use and peak demand found using the stochastic methods are consistently lower than found using the deterministic schedules. However, it is interesting to note that the settings of AS6 where all users were assumed to have a 75% dampening coefficient, resulted in a peak demand estimate that most closely matched the filtered sub-metered data. The total annual energy use was much more closely predicted by the DOE-2 and Business Hours schedules.

The general conclusion, though, is that the deterministic modeling can be very useful for predicting annual energy use, where the interaction of the occupants with the lighting system is considered in aggregate. After all, these deterministic schedules were determined based on

examining the aggregated data from multiple years and buildings. Similar to the issue of matching real-time daylight conditions with CIE standard skies, the usefulness of the deterministic simulations is restricted to long-term time horizons and should not be used to evaluate actual time-dependent valuations.

Conclusions from Validation Analysis

First, it should be noted that the validation analysis is based completely on the filtered sub-metered lighting energy data, which was filtered as described above from full-building lighting energy to an approximation of the energy use profile for the private offices only. As such, the validation effort should be understood to have been based on a best effort estimation of the actual energy use attributable to the private offices. To emphasize, no private office energy use data was available. However, as stated before, this type of reductionary assumption is not new in the energy modeling field, as building-specific occupancy patterns are often applied directly to specific spaces without regard to actual interior diversity.

Given the known limitations of the analysis, though, this initial validation effort provided valuable insight that enabled the shortcomings of the existing model infrastructure to be revealed. Namely, the rather restrictive profile of the occupancy model limited the general applicability of the combination of models. The occupancy model was built directly from the empirical data gathered from a single building (the LESO-EB in Lausanne, Switzerland), and as such the model's behavior is inextricably linked to that particular building.

As can be seen from the observed occupancy pattern, there are strong pattern behaviors that cannot be modified by simply adjusting the mobility parameter. For example, the drop in occupancy rate during lunchtime is a strong feature of this base occupancy model. However, the sub-metered data does not show that same extent of lunch period reduction, which could be due

to offset lunches which eliminate the compounding absences, lack of lunch breaks, or on-site lunch breaks which result in diversion of energy consumption to other spaces. However, though the sample building was known to have a cafeteria, it is unlikely that load was actually being diverted since the lighting in the cafeteria is likely on during non-lunch hours.

Additionally, the overnight occupancy rates in the sub-metered building must also be significantly higher than that seen in the building used to construct the occupancy model. Adjusting the mobility parameter mostly impacts the daytime occupancy pattern, shifting peak occupancy up or down with little influence on an already low-occupancy night pattern. Finally, the energy user patterns for the weekend days were in strong disagreement with the occupancy model, illustrating nearly opposite occupancy pattern predictions.

Overall, the results of the validation effort illustrate that the occupancy algorithm limited the applicability of the overall two-model combination due to the lack of available parameters to modify the occupancy profile. As such, an additional effort was undertaken to expand the existing occupancy model to allow additional free parameters to control this profile.

EXPANDED OCCUPANCY MODEL

As determined during the initial validation effort, the underlying occupancy model severely limited the range of possible combined model results. The only free parameter, the mobility parameter, simply adjusted the variability of the occupancy patterns, leading to more in-and-out events and reducing the total amount of time the space is actually occupied. Therefore, it was deemed desirable to adjust the occupancy algorithm to allow the use of additional parameters that would allow for flexible occupancy pattern shaping. This effort was focused solely on weekdays.

Base Occupancy Structure

The original occupancy model by Page et al. (2008)is herein referred to as the base occupancy model, or base algorithm.

The base algorithm is structured as described above. The general flow of the actual model execution begins with a randomized selection of one of twenty empirically-based probability of presence (POP) profiles. These weekly profiles are structured in 15-minute increments and provide the probability that the space is occupied at each specific time step. To execute the first order Markov-chain analysis, a set of state transition probabilities are generated at each time step based on the POPs and the mobility parameter. The current occupancy status is then determined based only on the previous occupancy status and the state transition probabilities.

Development of Additional Parameters

The goal of these proposed additional parameters was to facilitate additional flexibility that allowed the final occupancy profile to be adjusted to accommodate schedules and patterns that did not exist in the original test building. It was decided that the adjustments should be made to the POP arrays instead of during the calculation of the state transition probabilities, where the mobility parameter is applied. These additional parameters were intended to actually modify the base on which the state transition probabilities are determined, thus leaving the influence of the mobility parameter unmodified.

Four additional parameters were defined to assist with expanding the occupancy model to incorporate variations in the daily occupancy patterns. These four parameters, in order of execution, are the alpha, lambda, delta and nu parameters.

Alpha Parameter

The alpha parameter was the first parameter created. The alpha parameter simply aims to shift the beginning of the occupied day earlier or later. The base start time from the occupancy model was found to be approximately 6 am. At this time, the occupancy rate begins its steep climb toward midday. The alpha parameter shifts this occupancy start earlier or later in the day, and is structured to be input as the number of hours the start of the day should be delayed. For example, a shift of +2 would shift the start time to 8 am, and a shift of -1.75 would shift the start time to 4:15 am. Figure 58 illustrates the desired way in which the alpha parameter shifts the entire day pattern simple forward or backward without modifying the values.

When the alpha parameter is positive and the start of the day is shifted later, the POP is modified by carrying the same probability from the base start time (6 am) to the revised start time. The remainder of the day simply experiences a uniform time shift. Likewise, a negative

alpha parameter shifts the day earlier. In this case, the morning POP is truncated at the adjusted

start to the day, and then the remainder of the known day simply shifts forward. The last few

hours of the day are extended by simply repeating the probability from the final time step of the

unmodified algorithm until the day is complete.
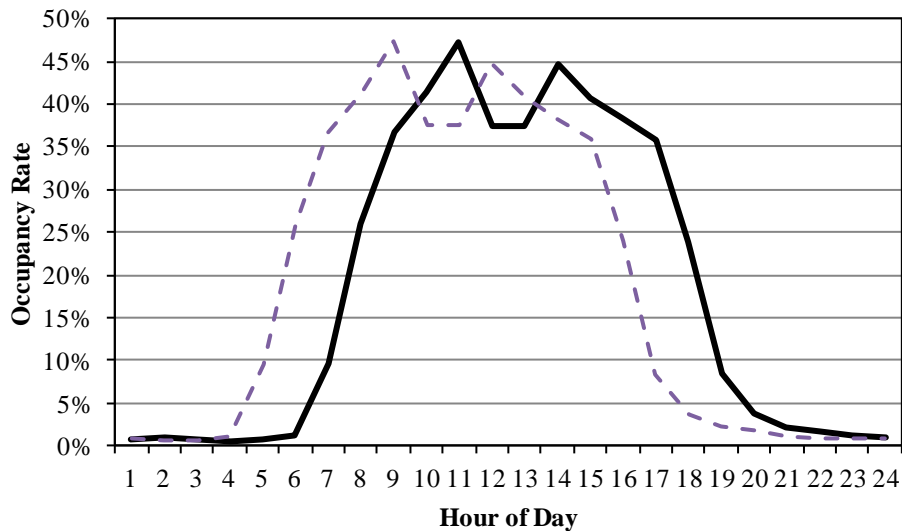
Figure 58: Desired shift by alpha parameter to occupancy model results.

Lambda Parameter

The lambda parameter was the second parameter created. The lambda parameter allows

the overall length of the day to be modified. The day length found in the base algorithm was 15

hours. The lambda parameters increases or decreases this day length, and is structured to be

input as the number of days by which the day length is lengthened. For example, a lambda of 2

indicates that the day should be lengthened by 2 hours to 17 hours total, and a lambda of -4

indicates that the day should be shortened by 4 hours to 11 hours total. Figure 59 illustrates this

desired shift.
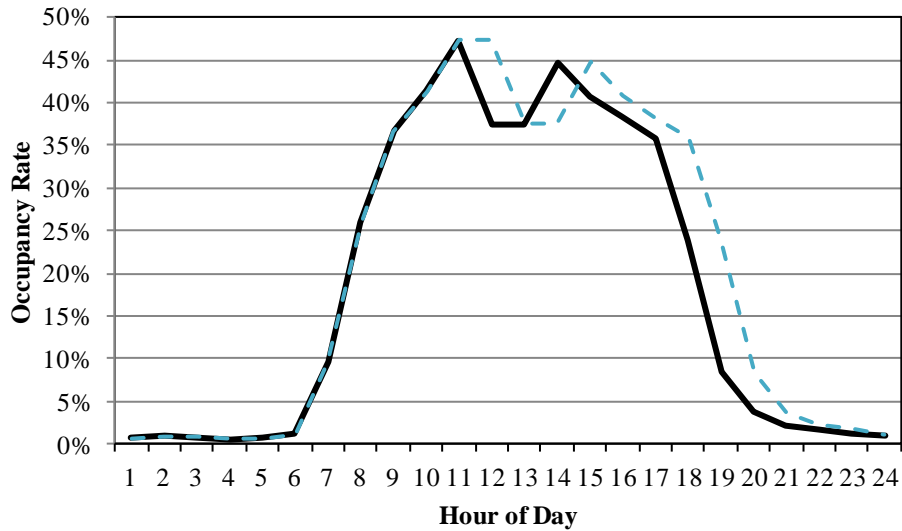
Figure 59: Desired shift of lambda parameter to occupancy model results.

The actual execution of the lambda shift began by establishing the actual times for the start and end of the day after the alpha shift, and the adjusted day length based on the lambda shift. The POP data is then either compressed or expanded to accommodate the change in day length. To execute this, linear interpolation is used to find data points at the specific time steps need at the conclusion of this modification. The shortfall of this method is that the extreme peaks and valleys of the unmodified POP data may get lost in the interpolation if the time step adjustment does not use the peak or valley values, and thus the extremes of occupancy may not be as prevalent, though the shift is fairly minor.

Delta Parameter

The delta parameter was then created to allow the adjustment of the daytime occupancy upward or downward. This parameter simply increases or decreases the probability of presence at each time step. The delta parameter is entered as a ratio of the current probability. For example, a delta of 1.2 increases the daytime POP values by 20%, and a delta of 0.8 decreases the daytime POP to 80% of their original value. The delta parameter again impacts only the

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daytime hours, which is assumed to be 6 am to 9 pm, but those time constraints are first adjusted according to the alpha and lambda parameters.

This is different from the mobility (mu) parameter in two ways. First, the delta parameter is applied only to the daytime occupied hours, where the mu parameter is applied to all hours of the day. Second, the mobility parameter impacts how the state transition probabilities are occurring, where the delta parameter simple scales the POPs that serve as the basis for the state transition probability calculations. The mu parameter captures the individual variation of occupancy patterns by allowing occupants to be more or less mobile, decreasing or increasing their sedentary occupation time. Figure 60 illustrates the desired impact of the delta parameter on the occupancy profile.
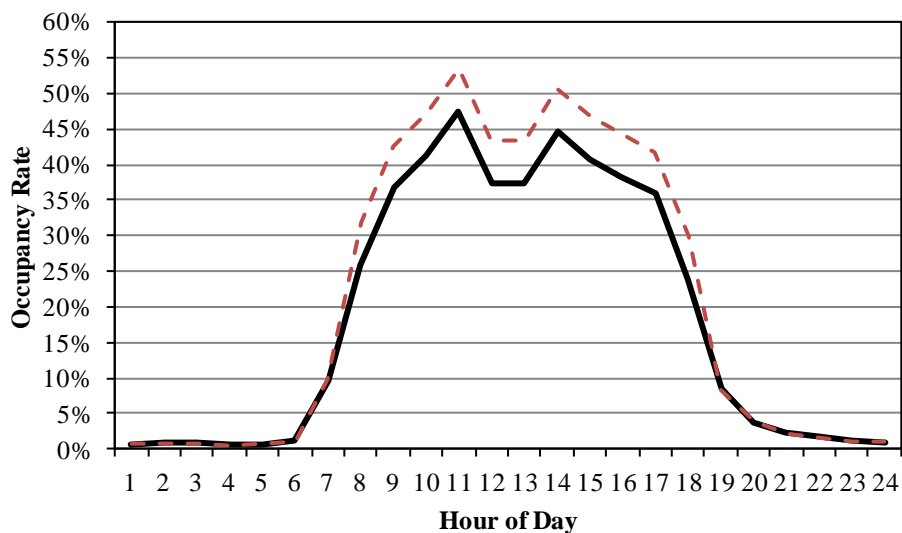
Figure 60: Desired shift of delta parameter to occupancy model results.

Nu parameter

Finally, the nu parameter was created to allow the adjustment of the occupancy rate outside of the normal daytime hours. This parameter is similar to the delta parameter in that it simply increases or decreases the probability of presence at each applicable time step. The nu

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parameter is again input as the ratio of the current probability during nighttime hours, the same

process that was demonstrated for the delta parameter. Figure 61 illustrates the desired shift

from the nu parameter.
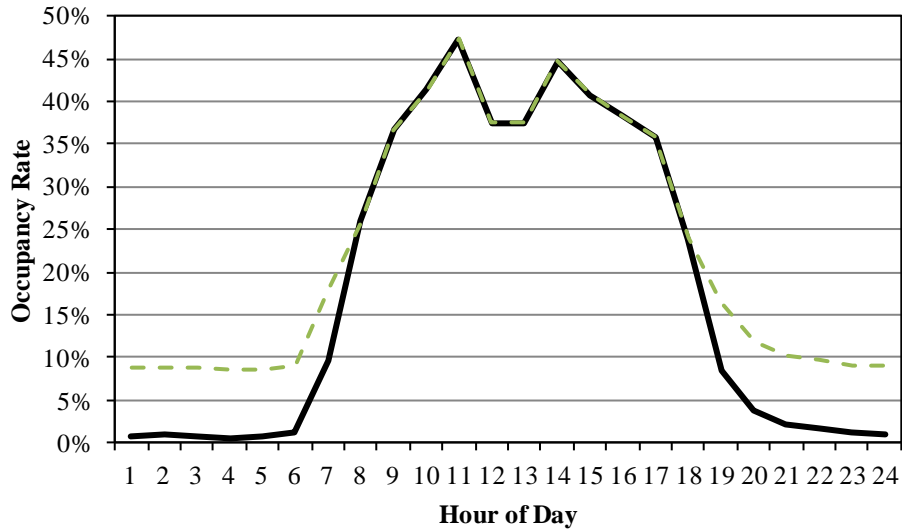
Figure 61: Desired shift of nu parameter to occupancy model results.

Programming and Sequencing

These additional model parameters were designed to be used to modify the POPs before

the mu parameter is applied and the state transition probabilities determined. Therefore, a

separate function was created in the Matlab simulation environment execute this modification to

the selected POP, which represents a full week of data. As stated above, the alpha parameter was

applied first, to shift the start of the day earlier or later. The lambda parameter was applied

second to increase or decrease the length of the day, with the start time based on the adjusted

start time dictated by the alpha parameter. The delta and nu parameters were then applied to the

daytime and nighttime hours, respectively, based on the workday start and end times after the

alpha and lambda shifts have occurred. The adjusted POP is then fed directly back into the

original algorithm.

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This method of incorporating these four new parameters was sequenced intentionally. The changes to the POPs do not influence the way in which the long-term absences are determined or the way in which the mobility parameter is applied. Those two important steps introduce the variability that was the most attractive feature of this particular algorithm, and introduction of these additional four parameters in another sequence would have modified how those particular adjustments were made.

Validation against Occupancy Profiles

The next step was to validate that the modifications introduced via the additional four parameters do not preclude the ability of the modified algorithm to model the same original occupancy profile. To demonstrate this, the modified algorithm was tested to convergence and compared against the results of the unmodified (or base) algorithm. Figure 62 illustrates this convergence test, showing results for both the modified algorithm and the base algorithm. As shown, at approximately 1,600 simulations, the models reach a similar result. There is however a drift after that period, leading to a small deviation between the results from the two algorithms in terms of annual occupied hours. Figure 63 presents a histogram comparing the results of the simulations using the base algorithm to that of the modified algorithm. As shown, even after the transformations have been included, the general distribution of the results is consistent with that of the base algorithm.
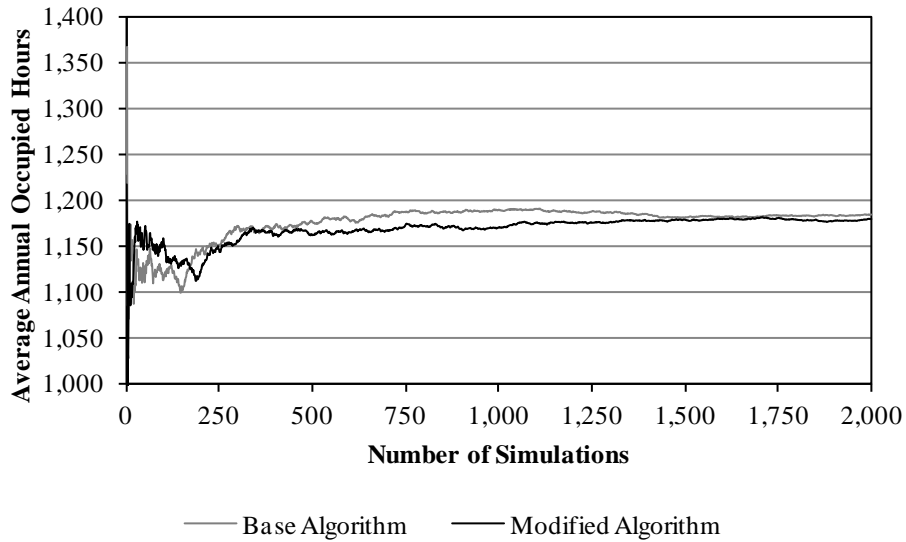
Figure 62: Determining model convergence for modified occupancy algorithm and comparing to model convergence for unmodified occupancy algorithm.
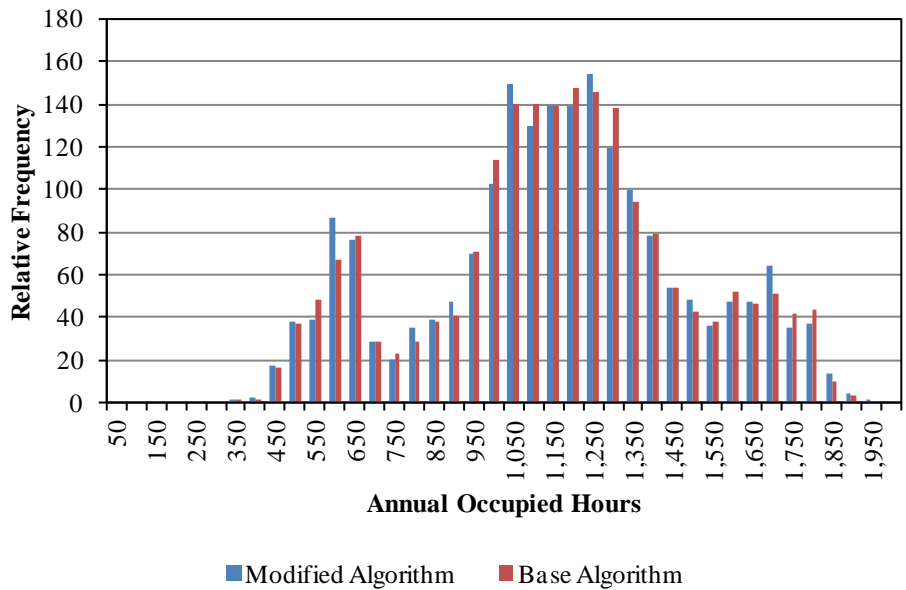
Figure 63: Plot illustrating relative frequency of simulation results for both the base (unmodified) occupancy algorithm and the modified occupancy algorithm.

Expanded Model Capabilities

The modified algorithm was then tested to evaluate the effectiveness of the four additional parameters in achieving the desired increased flexibility. Figures Figure 64 throughFigure 67 illustrate the actual impact of the four additional parameters on the POPs.
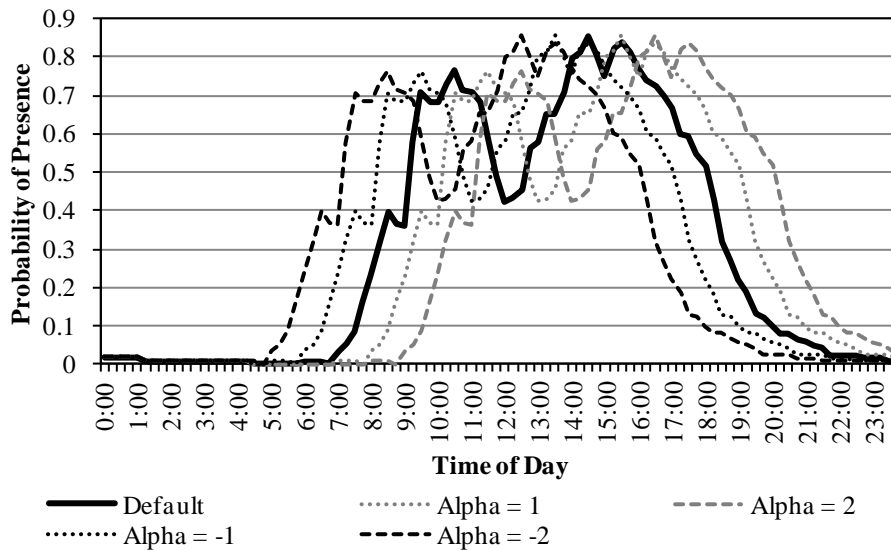
Figure 64: Impact of alpha parameter on probability of presence profile for a single day.
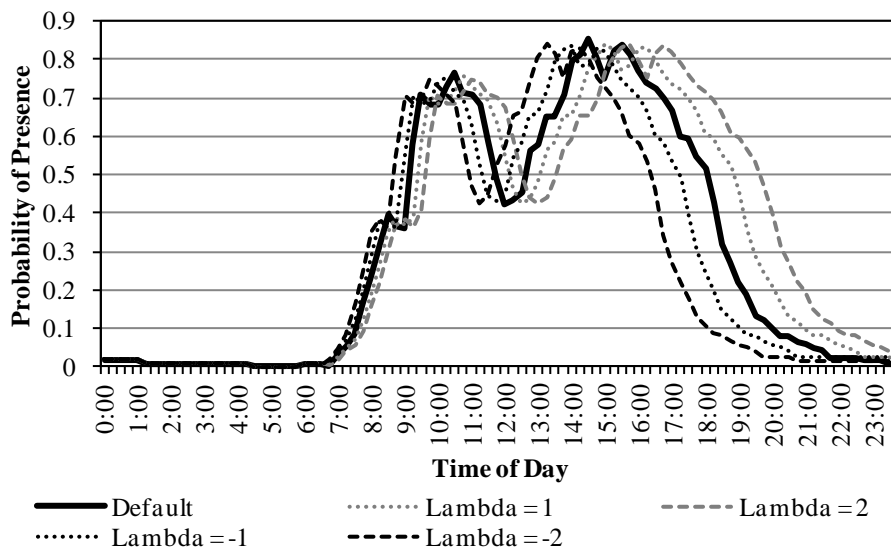
Figure 65: Impact of lambda parameter on probability of presence profile for a single day.
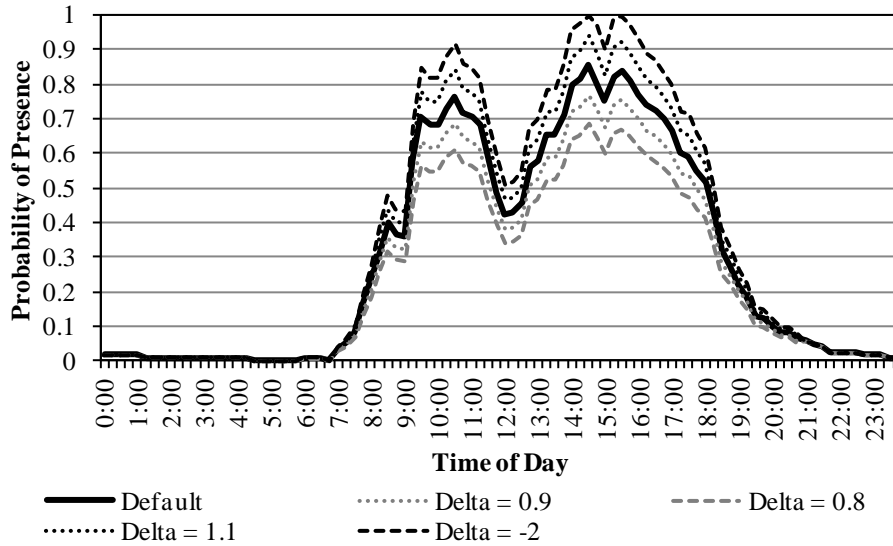
Figure 66: Impact of delta parameter on probability of presence profile for a single day.
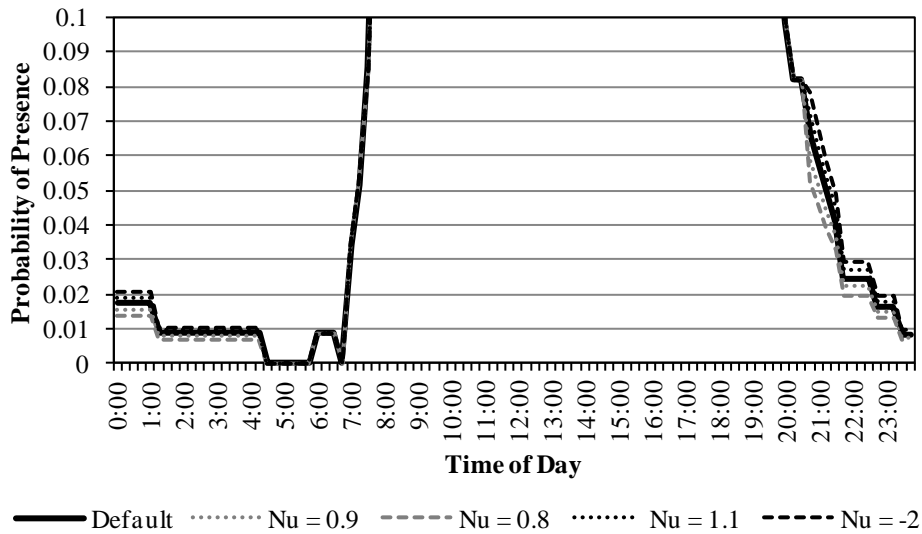
Figure 67: Impact of nu parameter on probability of presence profile for a single day (showing only below 10% due to scale of changes).
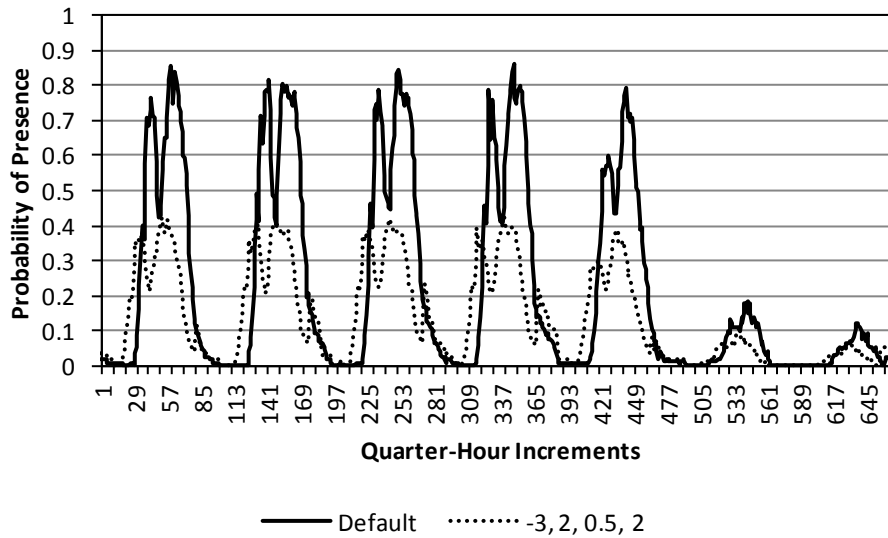
Figure 68: Impact of all four new occupancy model parameters on a weekly POP, with $\alpha = -3$, $\lambda = 2$, $\delta = 0.5$ and $\nu = 2$, beginning on Monday.

Figure 68 illustrates the impact of using all four new parameters on a weekly POP. As described, the alpha parameter was set to start the daytime occupancy pattern three hours earlier. The lambda parameter was set to extend the length of the daytime occupancy hours by two hours. The probability of presence during the peak daytime occupancy hours was reduced by half, and the overnight occupancy rate doubled. As shown, the parameters were successfully employed together to modify a weekly profile.

REVISED SENSITIVITY ANALYSIS

Using the revised and expanded occupancy model as described above, the sensitivity analysis was repeated to determine the relative importance of the various new and old parameters in contributing to the variance of annual energy use predictions. Again, the first-order Sensitivity Index and higher-order Total Index was determined for each parameter. Table 13 provides the results of this analysis. When examining the first-order effects (Si), the mobility parameter was again shown to most significantly contribute to the model variance. The sum of these first-order sensitivity indices is 0.771, illustrating that there are measurable interactions between these various parameters, making the Total Effect Index (St) a better measure.

Table 13: Results of revised sensitivity analysis.

	Dampening Coefficients				Occupancy Parameters				
	On	Off	Intermediate On	Intermediate Off	Mobility Parameter	Arrival Time	Day Length	Daytime Occupancy Rate	Nighttime Occupancy Rate
Si	0.016	0.123	0.063	0.105	0.244	0.064	0.018	0.137	0.001
St	0.320	0.645	0.356	0.681	1.214	0.544	0.452	0.822	0.319

Figure 69 illustrates the relative Total Effect Indices as determined using the same method outlined previously. As shown, the mobility parameter continues to most significantly contribute to the model variance, indicating again that the daily in-and-out, which directly impacts the ability to have switching actions, is of the largest importance.

It is interesting to note that the occupancy parameters, including the previously-established Mobility parameter and the four newly-proposed parameter, together account for 62.7% of the overall variance. This continues to reinforce the conclusion that a thorough method for assessing occupancy is pivotal in this analysis. Of those parameters, the mobility parameter proves to be the most significant, and that is followed by the daytime occupancy rate parameter

(delta) and the arrival time parameter (alpha). The nighttime occupancy rate parameter (nu) proves to be the least impactful, but that can be expected due to the overall low assumed nighttime occupancy rates.
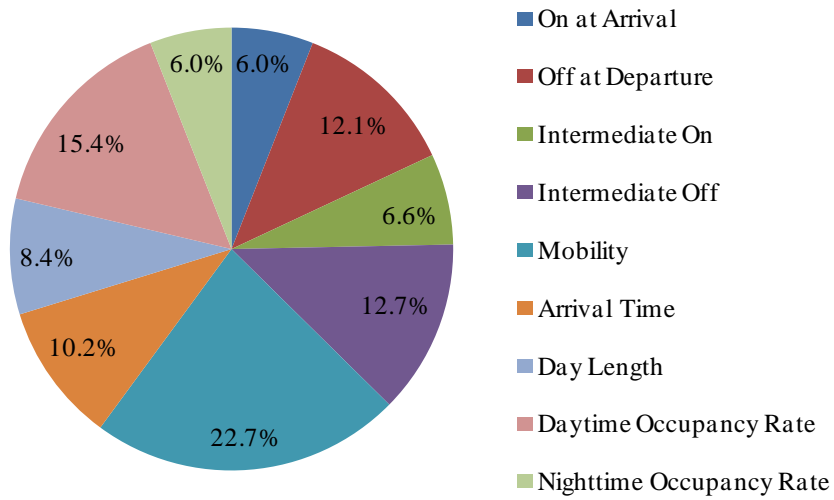
Figure 69: Relative total effect indicies using the expanded occupancy model.

REVISED VALIDATION ANALYSIS

Based on the adjusted occupancy algorithm, the validation was attempted again to see if the typical weekday, Saturday and Sunday daily profiles could be better matched given the added degrees of freedom in the occupancy model.
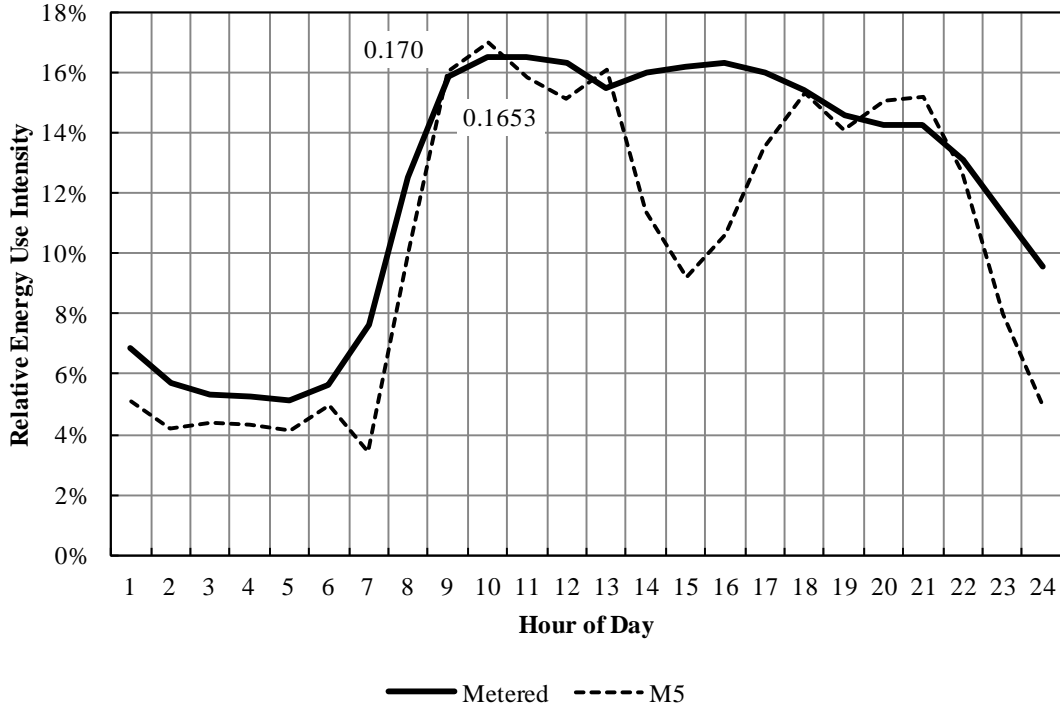
Figure 70: Results of revised validation for weekday.

Table 14: Additional model parameter settings for revised validation.

Parameter	Value
α	0
λ	6
δ	1
ν	20

Figure 70 illustrate the results of using the revised occupancy algorithm in the overall model flow. Table 14 includes the additional model parameters beyond Set 27 from the initial validation effort shown above, which served as the basis for this set (M5). As shown, the modifications to the occupancy profile allowed the overall energy use profile to be adjusted to provide more consistent agreement with the profile of the sub-metered lighting energy data. No adjustment was applied to the start time, though with further refinement, the start time could be pushed slightly later. The overall workday length was extended by six hours, allowing the peak daily occupied period to drift further toward the later hours. No adjustment was required for the peak-day occupancy, which follows since the peak-day lighting energy prediction from the base Set 27 was well able to predict though that time period. The overnight occupancy potential was increased by twenty times to significantly increase the overnight lighting energy use.

Figure 71 illustrates the results from this same revised validation set (M5) for Saturdays, and Figure 72 for Sundays, though the focus of these additional parameters was on the typical weekdays. As shown, the increase in occupancy potential during off-peak hours, which uniformly applies as currently written to weekdays as well as weekend days, paired with no change to the daytime occupancy potential served to invert the lighting energy profile, allowing it to more closely follow the shape of the sub-metered energy data. On both days, though, the prediction generally fell short of the sub-metered data results. Further refinements to this revised occupancy model could include overall scaling factors, one applied each to Saturday and one to Sunday, that are layered after the other four transformations. As stated at the beginning of this section, this validation effort and the tuning of the four new parameters focused solely on weekdays.

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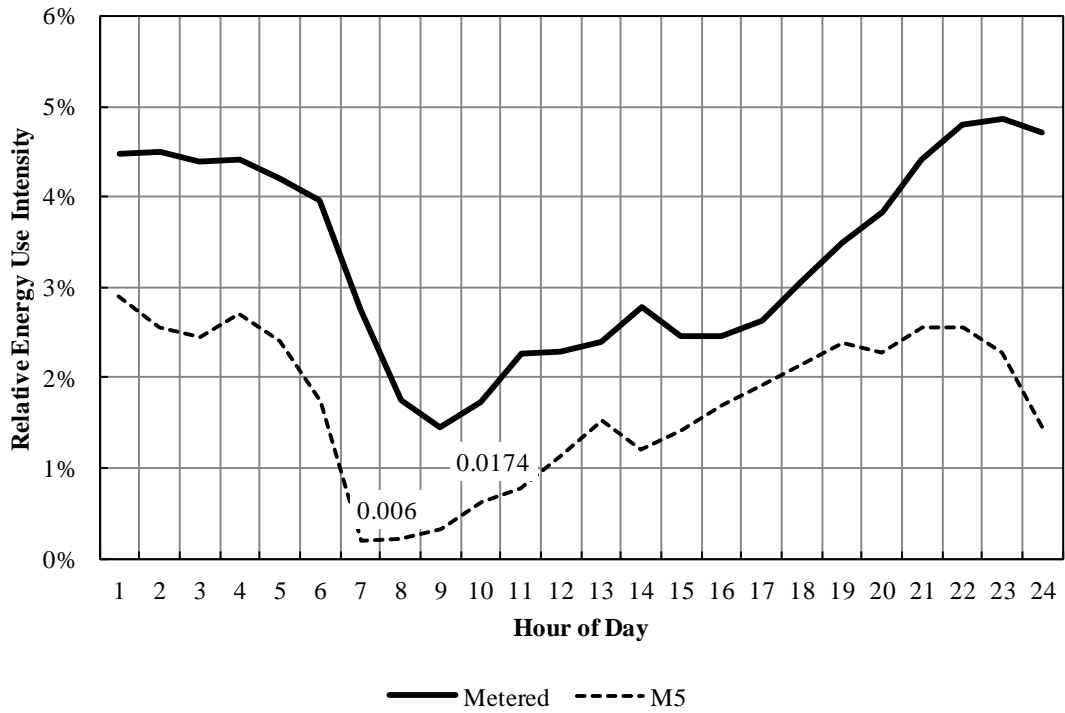
Figure 71: Results of revised validation for Saturday.
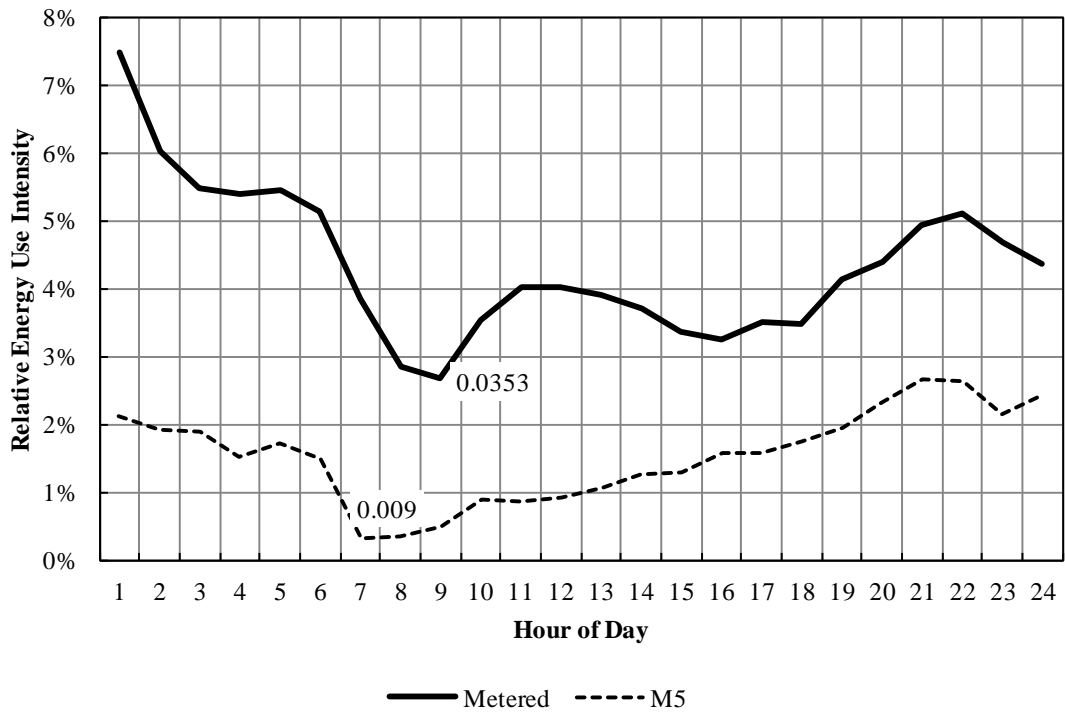
Figure 72: Results of revised validation for Sunday.

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DAYLIGHTING CALCULATION ASSUMPTION EXPLORATION

As presented earlier, the method of calculating the annual daylight availability for use in these lighting energy calculations are of interest, both because it directly influences the energy savings calculations for automated systems, but also because daylighting availability is the independent variable when considering the likelihood of manual control switching actions. As such, the method for creating an annual workplane illuminance profile was of particular interest.

Two-Sky Model

In previous work (Sanders & Chinnis, 2011), this particular issue had been a discussion topic. In that work, a method for eliminating the occurrence of partly cloudy sky conditions was used in the modeling effort, as illustrated in Figure 73.
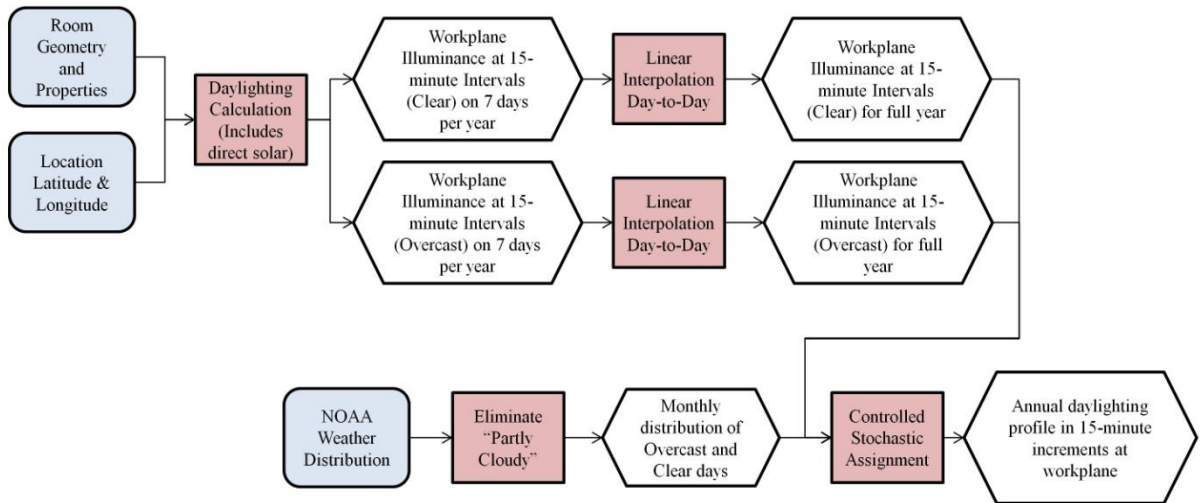
Figure 73: Two-sky model flow chart.

As shown, the first step of this modeling algorithm was to use the room geometry and location to perform an annual daylighting simulation by simulating the horizontal workplane illuminance under each clear and overcast standard skies, in 15-minute increments, on five days

per year (both Solstices and the 21st of each month between). Linear interpolation was then used

to extract the data from once per month to daily, accounting for daylight savings shifts. The

symmetry of the solar year was then exploited, while accounting for the asymmetry of daylight

savings time. Overall, this resulted in two annual daylighting profiles, one under clear skies and

one under overcast skies, that provided horizontal workplane illuminance in 15-minute

increments.

Simultaneously, weather data for the specific location was gathered in terms of sky type

for the specific location (NOAA Satellite and Information Service). The form of the data from

that source presents the typical monthly occurrence of each sky type (clear, overcast and partly

cloudy) based on historical data. In the two-sky model, the partly cloudy day type was

eliminated, assigning half of those days to be cloudy and half to be clear. Where an odd number

of partly cloudy days occurred, the sky type receiving the higher number was chosen randomly.

An annual daylight illuminance profile was then generated by using the weather data to

combine the annual overcast and clear sky illuminance profiles. For each day, the sky condition

was stochastically assigned to be clear or overcast. However, this stochastic assignment was

limited to verify that the number of occurrences per month of each sky type aligned with the

weather data. Then, using the two annual profiles created, the workplane illuminance if 15-

minute increments was determined for a full year.

Elimination of Partly Cloudy Conditions

In this method, the partly cloudy sky condition was eliminated. The purpose for this

elimination was to remove the very large variability of potential partly cloudy skies. In general,

the CIE recognizes a few partly cloudy sky models as described previously.   Those sky models

typically provide a uniform reduction in sky brightness over the overcast sky model and typically

simply reduce the direct-beam illumination. Other sky models include dense opaque cloud cover in certain locations, which may or may not occlude the direct sun. In general terms, when a partly cloudy sky is described as 60% cloud cover, that can be interpreted either as 60% of the sky covered in virtually opaque clouds or the full sky covered by a cloud that has the same effect as 60% of the overcast change. This overall confusion led to the elimination of the partly cloudy sky type from the previous work.

Three-Sky Model

To test the validity of the two-sky assumption, a three-sky model was also created an executed, and the difference in annual daylight availability and energy use predictions was evaluated. Figure 74 illustrates the flow of the three-sky model, except for the inclusion of the partly cloudy sky type in both the daylighting calculations and the weather assignment.
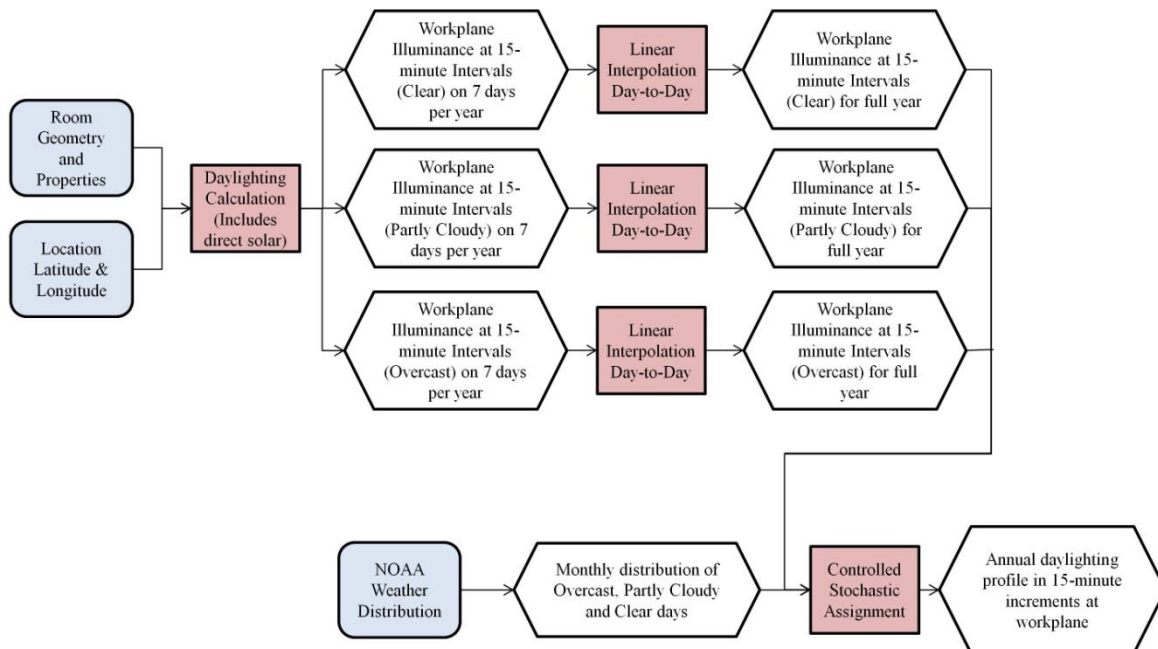
Figure 74: Three-sky model flow chart.

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One north-facing room and one south-facing room were modeled based on the subject building used for the validation effort above. The annual daylight availability, in fc-hours, was determined for each room under each sky model. Additionally, assuming the information from the validation study, the total annual energy density was also determined. Table 15 presents these results and Figure 75 illustrates the mean annual energy density calculation.

Table 15: Impact of daylighting model type on annual daylight availability and annual energy density

	Total Annual fc-Hours		Total Annual Energy Density	
	North	South	North	South
2-Step	129,100	311,017	0.080	0.112
3-Step	150,119	343,219	0.077	0.112
Difference	14.0%	9.4%	-3.2%	0.2%
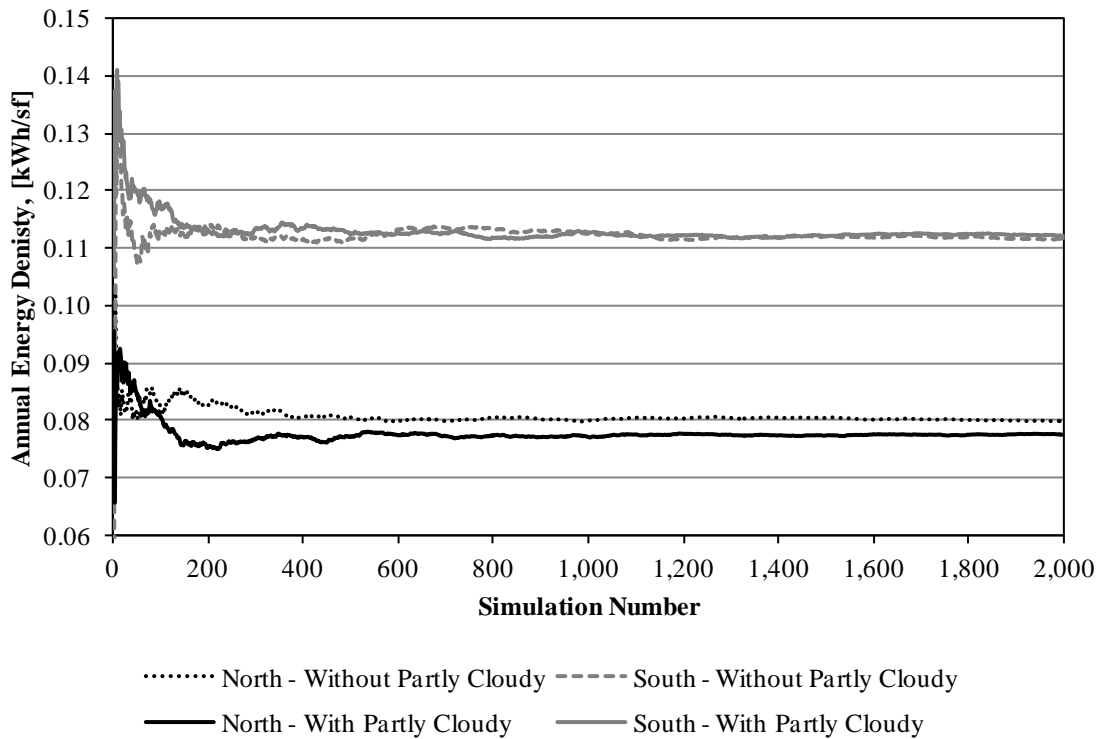
Figure 75: Impact of daylighting model type on annual energy density as a function of the number of simulations for each orientation.

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As shown, the difference in the annual energy density using the two methods of daylighting simulation was found to be statistically significant (p <0.05) for the North-facing room. The larger difference on the North-facing prediction is due to the reliance of the north-facing rooms on the luminance of the sky dome. Under a partly cloudy sky condition as modeled using a uniform brightness increase, the inclusion of that sky type increased the annual daylight availability. This in turn decreased the annual energy consumption since that daylight level was generally maintained below the blind-closing threshold of 2,000 lux (200 fc).

The difference in energy consumption for the South-facing room was not found to be statistically significant (p = 0.435). While the annual daylight availability did change, the resultant energy use was not significantly impacted since the illuminance levels were already exceeding the blind-closing thresholds for much of the year, thus the higher energy consumption than in the North-facing rooms.

Therefore, when considering the impact of this assumption on South-facing rooms, it was shown to be less imperative to include the partly cloudy sky condition in the modeling effort. Therefore, the revised validation analysis and deterministic modeling efforts were both performed using the three-sky model. However, despite the significant difference found between the two, it is not apparent which method provides results that are more accurate.

SUPPORT OF FUTURE WORK

This overall effort was intended to support future research into lighting energy predictions. The identification of an occupancy model and a lighting controls model to serve as the basis for dynamic lighting energy predictions can serve to focus future data collection efforts.

Capabilities of Extended Occupancy Model

The additional parameters added to the occupancy model constitute a significant contribution in the sense that the revised model provides the ability to generate occupancy profiles that are not directly tied to the subject building used to create the original algorithm. The extended occupancy model allows the occupancy pattern to be influenced by knowledge of the building operations, and allows the better tuning in general.

Additionally, supporting the modeling efforts in other fields, the addition of these four new degrees of freedom in the model may make manual tuning of energy modeling for auditing purposes more robust. If an energy modeler is participating in an inverse modeling effort, where known building parameters are matched against historical utility data and unknown factors such as scheduling are adjusted, the inclusion of additional degrees of freedom when incorporating stochastic occupancy patterns may allow nuanced adjustment of the modeling parameters. The results of this type of effort can be used to encourage occupant participation in energy use reduction should it be concluded that occupants were not maximizing the potential of their daylighting.

Data Collection for Simplified Modeling

The additional four parameters proposed for the occupancy model will also allow the base occupancy model to more simply be extended to space types that do not follow the same

schedule as the building used to derive the model. Employing the revised model with the four additional parameters would essentially be a simple data collection effort. The start time and typical day length can be simple adjustments based on the use patterns of the building, though the model is constructed to assume a standard pattern of occupied during the day and unoccupied nights and weekends. The daytime and nighttime occupancy rates can be surveyed through simple employee questionnaires or through the use of self-reported billing hours, for example. In this way, the four newly established parameters can be adjusted based on known occupancy patterns of the building, which will likely prove to be very useful in a reverse-modeling scenario. The mobility parameter is still a general unknown, though the original algorithm's authors suggest a standard set of high, medium and low values could be determined and published as a guide to users of their modeling infrastructure.

Data Collection Recommendations

The current occupancy and lighting controls algorithms, both modified in this effort, are still based on, and only truly applicable to, private office spaces. It is necessary to expand on these modeling capabilities to provide a more robust model structure.

Space Type Paradigms

A simple method to expand this model set to additional spaces is to group spaces into a few sets that operate with distinct behavior patterns.

Long-Term Private Spaces

The action probabilities incorporated into the Lightswitch-2002 model were based on data collected for private office spaces. While this data can prove very useful for modeling of space types where the users interact in a similar manner with the building system controls, it is effectively limited in its applicability because of that reliance. Additionally, the empirical basis

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for the blind control model proposed by Haldi & Robinson (Adaptive actions on shading devices in response to local visual stimuli, 2010) is based on private offices.

Moving forward, the basic probabilistic action curves used in the lighting controls model can be applied to spaces grouped as Long-term Private spaces. This broad group of spaces includes those that are occupied by one or perhaps two "controlling" individuals and that are not considered transient spaces. In these types of spaces, the impact of changing daylighting conditions is likely to have more of an impact compared to the same changing conditions in a space that is occupied only for short durations.

Long-term private spaces may also include such space types as residential living quarters and private offices, where only a single or a few occupants will be expected to use the controls and operate blinds. This control paradigm will also likely apply to space types including classrooms, where the teacher generally assumes ownership over the space controls, and conference rooms, where a single user, typically the presenter, does feel a strong level of "ownership" over the lighting.

Long-Term Public Spaces

In contrast to long-term private spaces, long-term public spaces are grouped based on the long personal occupancy periods but a general lack of ownership over the lighting controls. This is based on the concept of open office spaces, where the switching actions likely take place at first arrival and final departure, without adjustments being made throughout the day in response to short-term absences or changing daylight conditions as found in the work of Hunt (1979). In a long-term public space, it is assumed that the deterministic action on shading devices does not happen at each intermediate arrival or departure, but instead is likely triggered only by a closing of the shading device in the presence of average illuminance in excess of the UDI range.

While this paradigm is based on the open-office model, there are other space types that will likely behave this way, including libraries, retail and cafeterias. In general, these space types are assumed to follow this paradigm of multiple long-term occupants without a single occupant feeling "ownership" over the lighting system. Instead, the democracy of these types of spaces is assumed to lead to a general latency in control.

Expanding on the combined occupancy and lighting model for long-term private spaces and based on the results of Hunt (1979), it is assumed that in this space type will essentially ignore intermediate event probabilities. This results in a scenario where the lighting switch-on actions are likely only at first arrival and switch-off actions likely only at final departure.

Short-Term Spaces

Finally, the remaining spaces in building are assumed to be applicable to a typical group based on short-term occupancy. This includes such space types as restrooms, corridors, storage areas, and stairwells, where lighting needs are transitory. For many of the spaces, the lighting system status will likely exhibit inertial tendencies, trending to remain in their previous status for long periods of time independent of occupancy level. This is assumed to be most likely in spaces such as corridors and stairwells, where there is little personal "ownership" over the control system. For spaces such as restrooms and storage areas, there is assumed to be a higher level of personal "ownership" and therefore the lighting system status is likely to be more directly linked to the actual occupancy levels and patterns.

Similar to long-term public spaces, it is assumed that intermediate actions are likely irrelevant, since the occupancy state persists for such little time. Additionally, the dampening coefficients, specifically for the switch-off probability, will be important to consider, lending further inertial behavior to the space types with lower levels of ownership.

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Additionally, the thresholds for blind control and will need to be adjusted for short-term spaces. The range of tolerated daylight levels in these types of spaces is generally larger than for other space types, so therefore the thresholds should be adjusted to follow suit. This does not impact the deterministic yes/no shade action model, but simply modifies the levels at which those actions take place.

Occupancy-Focused Efforts

The extension presented herein for the occupancy model that allows the typical daily occupancy profile to be adjusted by controlling the background probability of presence data represents a convenient method for inverse modeling to compare energy user predictions to actual data sets. However, moving forward, the actual empirical data set should be expanded to allow various occupancy model parameters to be informed by these spaces.

The data collection efforts involved to support the empirically-based expansion of the occupancy model may be straightforward considering specific lighting controls, environmental conditions and overall patterns. In general, it would be most beneficial to sample occupancy patterns in many different actual spaces that fall within a particular space type paradigm. For example, the data set for the Long-Term Private Spaces set should not be based only on private offices, but should include diversity of application type.

The pure occupancy data collected is fairly simple, collecting simple "occupied/not occupied" time-stamped data streams in multiple spaces. This is most straightforward in spaces with only one entrance or exit. However, based on the work of others (Dodier, Henze, Tiller, & Guo, 2006), the data series from multiple sensor locations in a single space can be combined to create one binary occupancy series.

The data would be filtered to a time-series appropriate for model extension, for example identifying in 15-minute increments the status (occupied/not occupied) of the space. The analysis required to incorporate this data into the occupancy algorithm would involve assessing the patterns for probability of extended absence and probability of presence, which serve as the underlying empirical basis for the algorithm.

Post-hoc analysis of the probability of presence profiles determined in each space may support or refute the space type paradigms, further guiding the refinement of the models created. Additionally, further possible degrees of freedom, such as adjustment of day/night occupancy levels for Saturdays and Sundays separately from each other and weekdays, should be considered to allow extensive refinement of the occupancy model. Finally, a control parameter should be included to structure break times, such as lunch breaks, controlling their time, duration and depth.

Blind Control Actions

The work of Haldi & Robinson (Adaptive actions on shading devices in response to local visual stimuli, 2010) presented an advancement in manual blind control modeling beyond the basic control model used in this effort. Their method, though, tied the applicability of the model to daylighting conditions very specific to that particular building, including the dual-blind configuration, the electronic controls, and the fact that the building occupants are likely more aware of their controls due to extensive controls testing.

However, to further adapt modeling efforts to other space types, the empirical basis for this specific model structure of blind control should be expanded to additional space types paradigms through expanded data collection efforts. Additional window configurations, such as single windows facing in various directions, should be considered. Various curtain and blind

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types and controls should also be considered. The data set required for this analysis would include the paired interior and exterior illuminances, and the status of the blinds. For electronically-controlled blinds, the status can be taken from the control signal, as was done in the original work. For manual blinds, where both total deployment and angle of deployment can be varied, the status would need to be taken either through a sensor detection network or through the use of photographic equipment, which would likely be more cost-effective.

Lighting Controls Actions

Based on the results of the sensitivity analysis, some guidance can be provided to control the effectiveness of the data collection effort. The data collection effort should focus on three specific items: occupancy status, workplane illuminance and lighting power.

The results of the three focused efforts would need to be used in conjunction to evaluate the use of lighting action curves and dampening coefficients. Occupancy status should be tracked for all switching events, along with the daylighting conditions, to extract whether significant relationships exist between occupancy status, daylighting level and switching probability across space types. Again, this will allow the assumptions of the space type paradigms to be assessed.

Distribution of Data Collection Efforts

To maximize the cost-effectiveness of data collection efforts, the choice of sensor locations and types should specifically support further model developments. Between the occupancy, blind control and lighting control models, the following data is required:

- Occupancy data: binary occupancy data streams, time-stamped. For large multi-occupant spaces, disparate data streams would need to be merged to a single occupancy stream.

- Exterior horizontal illuminance.

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- Workplane illuminance. In multi-occupant spaces, workplane illuminance should be measured in locations representative of each lighting control zone.

- Blind status.

- Lighting energy status, per zone. If the luminaires dimmed per circuit, the lighting energy status should be based on actual metered power and not approximated by measuring lamp brightness due to ballast inefficiencies.

In general, all three major models rely on this same set of data. The occupancy data is the most critical data set, since it serves as the empirical basis directly for the occupancy models and indirectly for the lighting controls actions and blind models. Secondary to the occupancy status is the workplane illuminance and lighting energy status, which both serve as the empirical basis for the lighting controls action probabilities. The workplane illuminance is also a critical component of the blind control models. The blind status and the exterior illuminance, finally, are used directly in the blind model alone.

CONCLUSION

Overall, this research effort illustrated that the available simulation tools for estimating annual lighting energy use and peak demand result in widely-varied predictions. Additionally, the more informed the model is by the actual building, such as its actual LPD or hours of operation, the more accurate the prediction can be. In order for design-phase cost-benefit analysis to be performed, it is desirable to provide more robust modeling methods that better account for time-dependent variations, such as the advanced simulation methods. However, its current limitation to private offices reduces its applicability to the entire building due to variations in operational characteristics.

Additionally, this effort presented an adjusted method of predicting time-dependent lighting energy use at the occupant level, which would be desirable to integrate into whole-building energy simulations to coordinate window, blind, and switching actions, and their impact on HVAC systems and renewable energy resources. However, these models are very limited, having been based each on only a limited data set, and are not robust enough to model spaces with different occupancy patterns than the one used to form the model basis.

Recommendations

Going forward, this type of stochastic occupant-based modeling represents an opportunity to significantly expand the ability to characterize building energy use with high fidelity. From a utility perspective, the opportunity to understand the reasonable range of expected lighting energy use could create the opportunity to shift billing focus away from energy and demand charges alone and toward real-time energy performance. Figure 76 illustrates the range of intensity values found through the revised validation effort for a typical weekday. This

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figure depicts the absolute maximum and minimum energy use intensity predicted for each time step, as well as curves illustrating the location of one and two standard deviations above and below the mean.
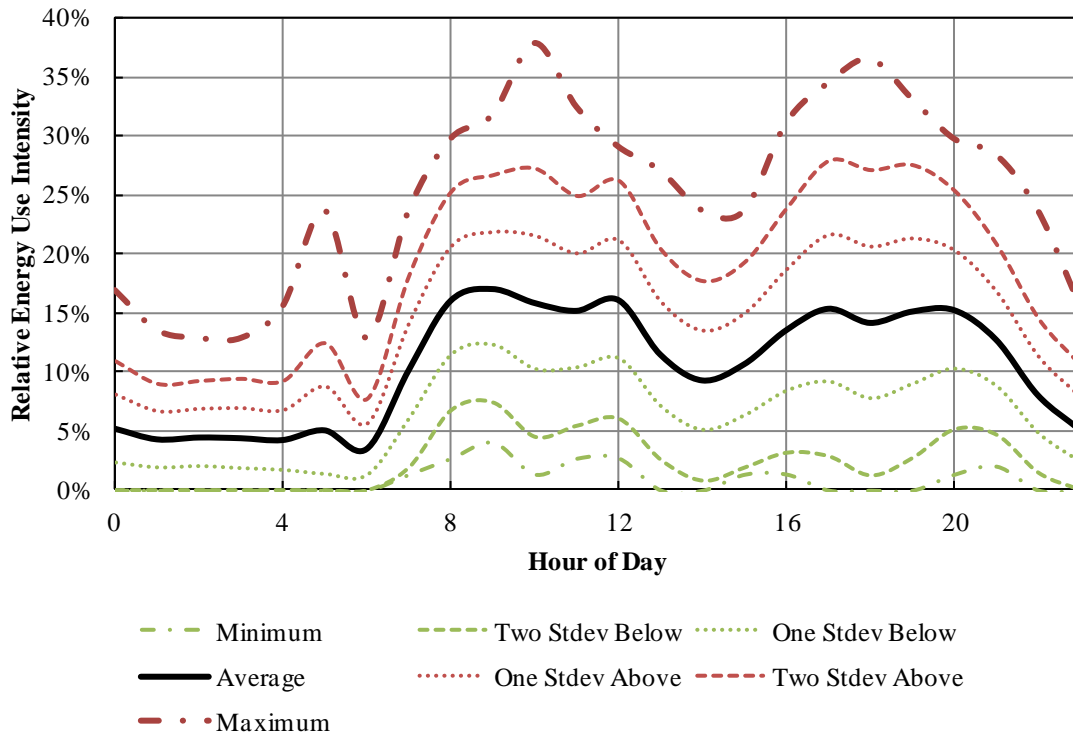
Figure 76: Range of simulated energy use intensity from revised validation for weekday.

Figure 77 illustrates the range of individual hourly values used to derive the distribution curves shown in Figure 76, but includes both weekdays and weekend days. As shown, the hourly use values do tend to distribute fairly uniformly above and below the mean hourly value, shown in red. It is also interesting to note that the hours at the beginning of the occupied day tend to experience larger variations in energy use intensity compared to the afternoon hours. Additionally, it is interesting to note that the lunch break seems to occur very typically, including at the highest and lowest energy consumption rates.

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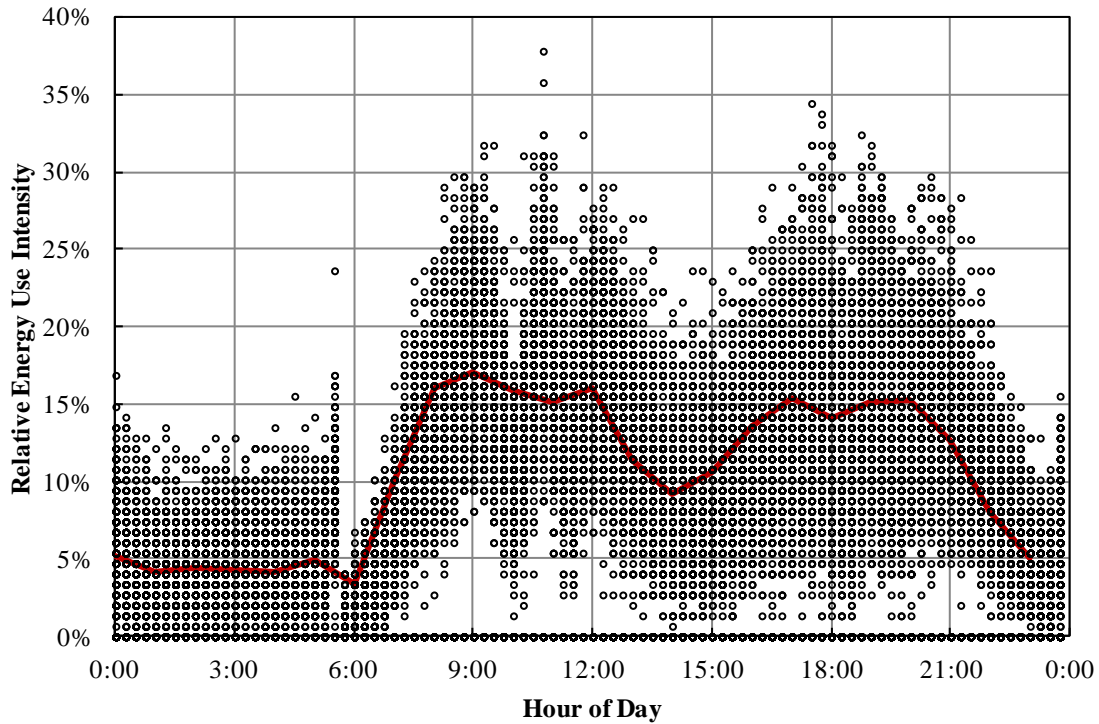
Figure 77: Individual values of simulated energy use intensity from revised validation for weekday for a single occupant over a single year (includes weekdays and weekend days).

This type of known hourly energy prediction for particular building type would be very useful when considering dynamic real-time pricing. Essentially, the utility could structure rates or tariffs to be based on where a building's energy consumption pattern lies on this type of predicted curve. If it consistently performs below the mean, incentives could be applied. If they consistently perform above the mean but within reasonable limits, minor incentives could be introduced to reduce energy or retro-commissioning could be offered. If operation regularly exceeds the maximum expected value, rates could be increased.

Additionally, the use of this type of hourly energy prediction tool can change the way in which energy efficiency measures are evaluated. For example, the California Energy Commission requires that cost-effectiveness of an energy efficiency measure be validated through the use of Time-Dependent Valuation (TDV) (California Energy Commission, 2004).

To support those calculations, hourly energy costs are determined that essentially capture 15 years worth of energy costs, including inflation and escalation, on an hourly basis. The TDV values capture both the energy costs and demand charges associated with time-of-use pricing. The TDV method, therefore, illustrates that peak-summer daytime electricity use is more expensive than winter nighttime use. To illustrate the potential impact of a stochastic simulation as the source for schedules, an analysis was performed to determine the 15-uear cost as a function of each of the three deterministic schedules reviewed, the results of the revised validation effort using the modified occupancy algorithm, and the filtered sub-metered lighting energy data. This analysis was performed using the TDV data for each of the 15 climate zones in California, and then averaged to arrived at the costs shown in Figure 78. As shown, the three deterministic schedules (Business Hours, ACM and DOE2) result in a 15-year energy cost that is significantly below the cost found using the filtered sub-metered data. The energy use predicted using the advanced simulation methods herein proposed result in an estimation that is much closer.
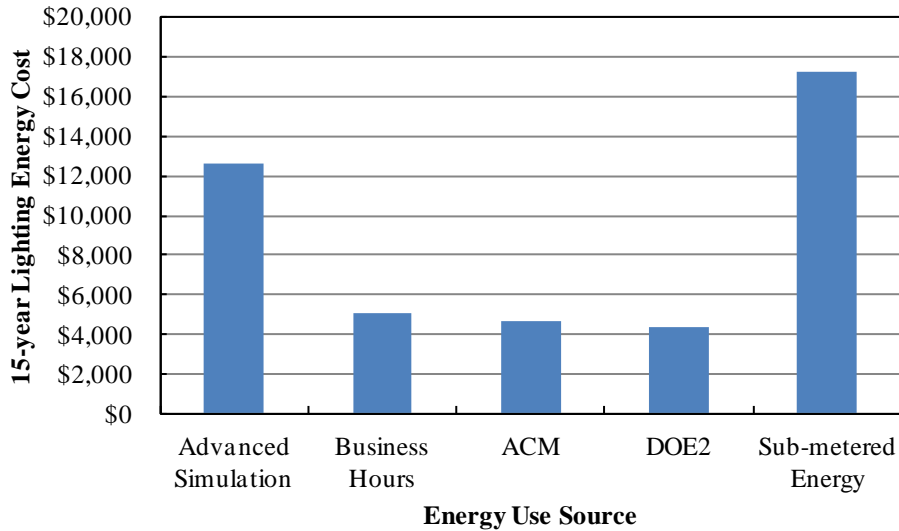
Figure 78: 15-year lighting energy costs as a function of various schedule sources using the TDV method.

As shown, the modeling methods proposed herein represent a marked improvement over existing deterministic scheduling options as a method to predict time-dependent lighting energy use. The ability to better predict lighting energy use will increase the accuracy of lighting energy predictions, leading to more accurate assessment of energy efficiency measures and cost effectiveness. Overall, this type of modeling capability could lead to an expanded way in which our lighting energy is viewed by the consumer and utility.

Overall, this effort marked a step in the effort to improve the accuracy of lighting energy modeling for both pre-design and post-occupancy assessments. An existing lighting energy model, the Lightswitch-2002 (Reinhart C. , 2004) model, was reviewed and updated given the most recent lighting controls and blind actions. Additionally, occupancy models were reviewed and it was determined that the Page et al. (2008) occupancy algorithm provided the most robust occupancy predictions for single-occupant offices. The combination of these two models was used to assess their potential for simulating lighting energy use, including a validation analysis

comparing the results to sub-metered lighting energy data for an office building, and a sensitivity analysis was performed using these two models to assess the relative impact of the individual parameters on the lighting energy prediction. It was found that the limitations of the occupancy profile restricted the range of applicability of the combined model set, so additional parameters to modify the occupancy model were proposed and assessed through validation and sensitivity analyses. The results of these analyses were used to construct data collection recommendations to allow the empirical data set on which the models are built to be expanded to allow the model combination to evolve to apply to more space types and incorporate a broader data set. The main contribution of this work was the identification and evaluation of various modeling options that present a potential for improving lighting energy prediction accuracy, and the distillation of the results of that analysis to a data collection recommendation that will be essential for expanding the model applicability.

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APPENDIX A: MAIN MATLAB SIMULATION CODE

```
%****************************************************************************
%
%   FUNCTION
%   LtgNrg
%
%   DESCRIPTION
%   Generates a new occupancy profile via Page and executes manual portions
of Lightswitch 2.0 model
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years
%
%   nZones: the number of single-occupancy zones
%
%   OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%   1 in increments of 0.01)
%
%   OffDC: Dampening coefficient for switch-on at departure conditions (0
%   to 1 in increments of 0.01)
%
%   IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%   to 1 in increments of 0.1)
%
%   IntOffDC: Dampening coefficient for intermediate switch-on conditions
%   (0 to 1 in increments of 0.1)
%
%   IntOnType: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%   WPE: Average workplane illuminance in 15-minute intervals
%
%   TargetE: Target illuminance
%
%   LPD: Lighting power density
%
%   ControlSys:   Lighting Control System where:
%       1 = Manual On/Manual Off, No Daylighting
%       2 = Manual On/Auto Off, No Daylighting
%       3 = Auto On/Auto Off, No Daylighting
%       4 = Manul On/Manual Off, With Daylight Dimming
%       5 = Manual On/Auto Off, With Daylight Dimming
%       6 = Auto On/Auto Off, With Daylight Dimming
%       7 = Manual On/Manual Off, With Daylight Bi-Level Switching
%       8 = Manual On/Auto Off, with Daylight Bi-Level Switching
%       9 = Auto On/Auto Off, with Daylight Bi-Level Switching
%       10 = Bi-level (50% Auto On, 50% Manual On/All Auto Off, No Daylight
%
%   DelayTime: Occ Sensor Delay Time in minutes
%
%   BlindControl:   Type of blind controls where:
%       1 = Fully manual
%       2 = Fully automated (ideal)
%
```

```
%    OUTPUT
%    LtgNrgOut: Effective 15-minute LPD
%
%
%
%    ORIGINAL AUTHOR
%    Darcie Chinnis
%    University of Colorado
%    darcie.oconnor@colorado.edu
%
%    NOTES
%
%
%************************************************************************
function NrgOut =
LtgNrg(year,nZones,TargetE,LPD,ControlSys,DelayTime,BlindControl,mu)

%Call Page algorithm to create occupancy profiles
OccProfile = generateOccupancyMinIntervalsVariableMu(year,nZones,mu);

%Dim main variables
BlindStatus(1:nZones,1:35040)=0;
LtgStatus(1:nZones,1:35040)=0;
BlindStatus(1:nZones,1)=0;
AnnualIntensity(1:nZones)=0;
NrgProfile(1:nZones,2:35041)=0;
AnnualProfile(2:35041,1:nZones)=0;
TotalProfile(2:35041,1)=0;

%for each zone, loop through manual control algorithm
for n = 1:nZones;

    %Call lightswitch 2.0 model
    NrgProfile=
LightSwitch(OccProfile,TargetE,n,ControlSys,DelayTime,BlindControl,BlindStatu
s);

    %Calculate effective Use
    for j = 2:35041

        AnnualIntensity(n)=AnnualIntensity(n)+NrgProfile(j,n);

    end

    AnnualEnergy(n)=LPD*AnnualIntensity(n)

    AnnualProfile(2:35041,n)=NrgProfile(2:35041,n);

end

for j=2:35041
    for n = 1:nZones
        TotalProfile(j,1)=TotalProfile(j,1)+AnnualProfile(j,n);
    end
end
```

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```
save('TotalProfile.mat');
```

```
%*************************************************************************
%
%   FUNCTION
%   LtgNrgConv
%
%   DESCRIPTION
%   Generates a new occupancy profile via Page and executes manual portions
of Lightswitch 2.0 model
%   with fixed inputs, used to evaluate model convergence
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years
%
%   nZones: the number of single-occupancy zones
%
%   OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%   1 in increments of 0.01)
%
%   OffDC: Dampening coefficient for switch-on at departure conditions (0
%   to 1 in increments of 0.01)
%
%   IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%   to 1 in increments of 0.1)
%
%   IntOffDC: Dampening coefficient for intermediate switch-on conditions
%   (0 to 1 in increments of 0.1)
%
%   IntOnType: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%   WPE: Average workplane illuminance in 15-minute intervals
%
%   TargetE: Target illuminance
%
%   LPD: Lighting power density
%
%   ControlSys:    Lighting Control System where:
%       1 = Manual On/Manual Off, No Daylighting
%       2 = Manual On/Auto Off, No Daylighting
%       3 = Auto On/Auto Off, No Daylighting
%       4 = Manul On/Manual Off, With Daylight Dimming
%       5 = Manual On/Auto Off, With Daylight Dimming
%       6 = Auto On/Auto Off, With Daylight Dimming
%       7 = Manual On/Manual Off, With Daylight Bi-Level Switching
%       8 = Manual On/Auto Off, with Daylight Bi-Level Switching
%       9 = Auto On/Auto Off, with Daylight Bi-Level Switching
%       10 = Bi-level (50% Auto On, 50% Manual On/All Auto Off, No Daylight
%
%   DelayTime: Occ Sensor Delay Time in minutes
%
%   BlindControl:   Type of blind controls where:
%       1 = Fully manual
%       2 = Fully automated (ideal)
%
%   OUTPUT
%   LtgNrgOut: Effective 15-minute LPD
%
```

```matlab
%
%
%    ORIGINAL AUTHOR
%    Darcie Chinnis
%    University of Colorado
%    darcie.oconnor@colorado.edu
%
%    NOTES
%
%
%*************************************************************************
function NrgOutConv = LtgNrgConv()

year = 2011;
nZones = 1;
TargetE = 300;
LPD = 1;
ControlSys = 1;
DelayTime = 15;
BlindControl = 1;
mu = 0.040;

%Call Page algorithm to create occupancy profiles
OccProfile = generateOccupancyMinIntervalsVariableMu(year,nZones,mu);

%Dim main variables
BlindStatus(1:nZones,1:35040)=0;
LtgStatus(1:nZones,1:35040)=0;
BlindStatus(1:nZones,1)=0;
AnnualIntensity(1:nZones)=0;
NrgProfile(1:nZones,2:35041)=0;
AnnualProfile(2:35041,1:nZones)=0;
TotalProfile(2:35041,1)=0;




%for each zone, loop through manual control algorithm
for n = 1:nZones;

    %Call lightswitch 2.0 model
    NrgProfile=
LightSwitchConv(OccProfile,TargetE,n,ControlSys,DelayTime,BlindControl,BlindS
tatus);

    %Calculate effective Use
    for j = 2:35041

        AnnualIntensity(n)=AnnualIntensity(n)+NrgProfile(j,n);

    end

    AnnualEnergy(n)=LPD*AnnualIntensity(n)

    AnnualProfile(2:35041,n)=NrgProfile(2:35041,n);
```

```
end

for j=2:35041
    for n = 1:nZones
        TotalProfile(j,1)=TotalProfile(j,1)+AnnualProfile(j,n);
    end
end

save('TotalProfile.mat');

NrgOutConv = AnnualEnergy;
```

```
%*************************************************************************
%
%   FUNCTION
%   LtgNrgSA
%
%   DESCRIPTION
%   Generates a new occupancy profile via Page and executes manual portions
of Lightswitch 2.0 model
%   For use with Sensitivity Analysis (SA) Code
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years
%
%   nZones: the number of single-occupancy zones
%
%   OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%   1 in increments of 0.01)
%
%   OffDC: Dampening coefficient for switch-on at departure conditions (0
%   to 1 in increments of 0.01)
%
%   IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%   to 1 in increments of 0.1)
%
%   IntOffDC: Dampening coefficient for intermediate switch-on conditions
%   (0 to 1 in increments of 0.1)
%
%   IntOnType: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%   WPE: Average workplane illuminance in 15-minute intervals
%
%   TargetE: Target illuminance
%
%   LPD: Lighting power density
%
%   ControlSys:    Lighting Control System where:
%       1 = Manual On/Manual Off, No Daylighting
%       2 = Manual On/Auto Off, No Daylighting
%       3 = Auto On/Auto Off, No Daylighting
%       4 = Manul On/Manual Off, With Daylight Dimming
%       5 = Manual On/Auto Off, With Daylight Dimming
%       6 = Auto On/Auto Off, With Daylight Dimming
%       7 = Manual On/Manual Off, With Daylight Bi-Level Switching
%       8 = Manual On/Auto Off, with Daylight Bi-Level Switching
%       9 = Auto On/Auto Off, with Daylight Bi-Level Switching
%       10 = Bi-level (50% Auto On, 50% Manual On/All Auto Off, No Daylight
%
%   DelayTime: Occ Sensor Delay Time in minutes
%
%   BlindControl:   Type of blind controls where:
%       1 = Fully manual
%       2 = Fully automated (ideal)
%
%   OUTPUT
%   LtgNrgOut: Effective 15-minute LPD
```

```matlab
%
%
%
%   ORIGINAL AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.oconnor@colorado.edu
%
%   NOTES
%
%
%**************************************************************************
function NrgOutSA = LtgNrgSA(x)

OnDC=x(1);
IntOffDCP=x(2);
IntOnDC=x(3);
mu=1;
OffDC=x(4);


year = 2011;
nZones = 1;
TargetE = 300;
LPD = 1;
ControlSys=1;
DelayTime=15;
BlindControl=1;

%Call Page algorithm to create occupancy profiles
OccProfile = generateOccupancyMinIntervalsVariableMu(year,nZones,mu);

%Dim main variables
BlindStatus(1:nZones,1:35040)=0;
LtgStatus(1:nZones,1:35040)=0;
BlindStatus(1:nZones,1)=0;
AnnualIntensity(1:nZones)=0;
NrgProfile(1:nZones,2:35041)=0;
AnnualProfile(2:35041,1:nZones)=0;
TotalProfile(2:35041,1)=0;

%for each zone, loop through manual control algorithm
for n = 1:nZones;

    %Call lightswitch 2.0 model
    NrgProfile=
LightSwitchSA(OccProfile,TargetE,n,ControlSys,DelayTime,BlindControl,BlindSta
tus,OnDC,OffDC,IntOffDCP,IntOnDC);

    %Calculate effective Use
    for j = 2:35041

        AnnualIntensity(n)=AnnualIntensity(n)+NrgProfile(j,n);

    end
```

```
    NrgOutSA(n)=LPD*AnnualIntensity(n);

end
```

```
%*************************************************************************
%
%    FUNCTION
%    LtgNrgVA
%
%    DESCRIPTION
%    Generates a new occupancy profile via Page and executes manual portions
of Lightswitch 2.0 model
%    For use for creation of scatter plots
%
%    ARGUMENTS
%    year: the year that we are using; this program does not account for
%          leap-years
%
%    nZones: the number of single-occupancy zones
%
%    OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%    1 in increments of 0.01)
%
%    OffDC: Dampening coefficient for switch-on at departure conditions (0
%    to 1 in increments of 0.01)
%
%    IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%    to 1 in increments of 0.1)
%
%    IntOffDC: Dampening coefficient for intermediate switch-on conditions
%    (0 to 1 in increments of 0.1)
%
%    IntOnType: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%    WPE: Average workplane illuminance in 15-minute intervals
%
%    TargetE: Target illuminance
%
%    LPD: Lighting power density
%
%    ControlSys:    Lighting Control System where:
%        1 = Manual On/Manual Off, No Daylighting
%        2 = Manual On/Auto Off, No Daylighting
%        3 = Auto On/Auto Off, No Daylighting
%        4 = Manul On/Manual Off, With Daylight Dimming
%        5 = Manual On/Auto Off, With Daylight Dimming
%        6 = Auto On/Auto Off, With Daylight Dimming
%        7 = Manual On/Manual Off, With Daylight Bi-Level Switching
%        8 = Manual On/Auto Off, with Daylight Bi-Level Switching
%        9 = Auto On/Auto Off, with Daylight Bi-Level Switching
%        10 = Bi-level (50% Auto On, 50% Manual On/All Auto Off, No Daylight
%
%    DelayTime: Occ Sensor Delay Time in minutes
%
%    BlindControl:   Type of blind controls where:
%        1 = Fully manual
%        2 = Fully automated (ideal)
%
%    OUTPUT
%    LtgNrgOut: Effective 15-minute LPD
%
```

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```matlab
%
%
%    ORIGINAL AUTHOR
%    Darcie Chinnis
%    University of Colorado
%    darcie.oconnor@colorado.edu
%
%    NOTES
%
%
%**************************************************************************
function Analysis = LtgNrgVA(p)

%Dim main variables
BlindStatus(1,1:35040)=0;
LtgStatus(1,1:35040)=0;
BlindStatus(1,1)=0;
AnnualIntensity(1)=0;
NrgProfile(1,2:35041)=0;
AnnualProfile(2:35041,1)=0;
TotalProfile(2:35041,1)=0;

for a = 1:p;

    OnDC=rand;
    IntOffDCP=rand;
    IntOnDC=rand;
    mu=rand;
    OffDC=rand;

    year = 2011;
    nZones = 1;
    TargetE = 300;
    LPD = 1;
    ControlSys=1;
    DelayTime=15;
    BlindControl=1;

    %Call Page algorithm to create occupancy profiles
    OccProfile = generateOccupancyMinIntervalsVariableMu(year,nZones,mu);

    %Call lightswitch 2.0 model
    NrgProfile=
LightSwitchSA(OccProfile,TargetE,1,ControlSys,DelayTime,BlindControl,BlindSta
tus,OnDC,OffDC,IntOffDCP,IntOnDC);

    AnnualIntensity = 0;

    %Calculate effective Use
    for j = 2:35041

        AnnualIntensity=AnnualIntensity+NrgProfile(j,1);

    end
```

```matlab
    NrgOut=LPD*AnnualIntensity;


    Analysis(a,1:6)=[OnDC,OffDC,IntOnDC,IntOffDCP,mu,NrgOut];

end
```

```
%*************************************************************************
%
%   FUNCTION
%   generateOccupancyMinInterval
%
%   DESCRIPTION
%   Generates a new occupancy profile for the year specified. replaces
%   occupancy information in the input structure with new occupancy.
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years yet. [and energyplus would barf if it got anything
%         with more or less than 8760 values anyway...]
%
%   OUTPUT
%   occout: a structure containing the following:
%      .year
%      .month
%      .day
%      .hour
%      .minute
%      .val  = this is a fractional value of the total number of people
present;
%
%   ORIGINAL AUTHOR
%   Ryan Tanner
%   University of Colorado at Boulder
%   ryan.tanner@colorado.edu
%
%   ORIGINAL DATE
%   27.Mar.2011
%
%   MODIFICATION AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.chinnis@colorado.edu
%
%   NOTES
%   May.2011 Currently the occupancy algorithm generates data at 15-min
%   intervals and generates enough for exactly one year plus one increment
%   (34041 fifteen-minute intervals)
%
%   14.Sep.2011 Added some commenting.
%
%*************************************************************************

function occout = generateOccupancy(year,nzones)

load('SampleInputs.mat')
NumberOfBuildings=1;
NumberOfPeople=1;
% j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
time=(1:(8760*4))*15*60; % generate 15-minute intervals for a year [in
SECONDS]
```

```matlab
time=[time,8760*4*15*60+15*60]; % add one more interval to match occupancy
output from the Page programs
    occout.year(35041)  = 0;
    occout.month(35041) = 0;
    occout.day(35041)   = 0;
    occout.hour(35041)  = 0;
    occout.minute(35041)= 0;
    occout.val(nzones,35041)   = 0;


for zone = 1:nzones
    j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
    %generate 15-minute occupancy data using the Page Algorithm
    Occupancy=occtest(NumberOfBuildings,NumberOfPeople,...
    LongAbsences{j}.averagenumberperyear,...
    LongAbsences{j}.probability,...
    MuProfiles{j}.mean,...
    ProbabilityProfiles{j}.probability);
    month=1;
    day=1;
    hour=0;
    % mins=0;
    % sec=0;
    count=1;
    for ii=2:length(Occupancy)

        % create output values for year, month, day, hour and minute if at
        % exact hourly value
        if mod(time(ii),3600)==0; % if we're at an hourly value[1:00, 4:00,
15:00, etc...], this is true!,
            hour=hour+1;
            minute = 0;

            if hour > 24 % if we're at hour 25, we move to the next day,
first hour
                hour=1;
                day=day+1;

                if day > eomday(year, month) %eomday is the ending day of the
month: 31 for jan, mar, 28/29 for feb, 30 for april, etc.
                                            %if we're at day 32 for january,
move to february
                    day=1;
                    month=month+1;

                end

            end

        %create output values for year, month, day, hour and minute if NOT
        %at exact hourly value
        else
            %calculate minutes
            if ii == hour*4 + 1;
                minute = 15;
```

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```matlab
            elseif ii == hour*4 + 2;
                minute = 30;
            else ii == hour*4 + 3;
                minute = 45;
            end

        end %ends 15-minute loop

        % at this point we've established what year, month, day, and
        % hour and minute we are at.

        %within the hourly loop, set values for the occupancy output
        %structure
        occout.year(count)      = year;
        occout.month(count)     = month;
        occout.day(count)       = day;
        occout.hour(count)      = hour;
        occout.minute(count)    = minute;
        occout.val(zone,count)  = Occupancy(ii);

        % [ARTIFACT OF RYAN's MODEL]
        % Now comes the tricky part; how to turn 15-minute data into
        % hourly data? As of this revision, we take the average of
        % occupancy over the last four 15-minute intervals, and round
        % that number up with the 'ceil' command. Then we divide by the
        % total number of people to get a fractional value of total
        % occupancy, (between zero and 1, naturally) which Energyplus
        % can interpret and multiply by an occupant density to get the
        % right number of people.
        % occout.val(zone,count)  = ceil(mean(Occupancy(ii-
3:ii)))/NumberOfPeople;

        if count==35041; %stop when we get to the end of the year
            break
        end

        count=count+1;

    end % of looping through 34041 occupancy entries

end % of zonal loop

OccProfile=occout.val;

end % of function
```

```
%**************************************************************************
%
%   FUNCTION
%   generateOccupancyMinIntervalsVariableMu
%
%   DESCRIPTION
%   Generates a new occupancy profile for the year specified. replaces
%   occupancy information in the input structure with new occupancy.  Allows
mu parameter to be input value (overrides built-in selection methodology).
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years yet. [and energyplus would barf if it got anything
%         with more or less than 8760 values anyway...]
%
%   OUTPUT
%   occout: a structure containing the following:
%      .year
%      .month
%      .day
%      .hour
%      .minute
%      .val  = this is a fractional value of the total number of people
present;
%
%   ORIGINAL AUTHOR
%   Ryan Tanner
%   University of Colorado at Boulder
%   ryan.tanner@colorado.edu
%
%   ORIGINAL DATE
%   27.Mar.2011
%
%   MODIFICATION AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.oconnor@colorado.edu
%
%   NOTES
%   May.2011 Currently the occupancy algorithm generates data at 15-min
%   intervals and generates enough for exactly one year plus one increment
%   (34041 fifteen-minute intervals)
%
%   14.Sep.2011 Added some commenting.
%
%   2.14.2012   Fixed mu parameter as input
%
%**************************************************************************

function occout = generateOccupancy(year,nzones,mu)

load('SampleInputs.mat')
NumberOfBuildings=1;
NumberOfPeople=1;
```

```matlab
% j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
time=(1:(8760*4))*15*60; % generate 15-minute intervals for a year [in
SECONDS]
time=[time,8760*4*15*60+15*60]; % add one more interval to match occupancy
output from the Page programs
    occout.year(35041)  = 0;
    occout.month(35041) = 0;
    occout.day(35041)   = 0;
    occout.hour(35041)  = 0;
    occout.minute(35041)= 0;
    occout.val(nzones,35041)   = 0;

for zone = 1:nzones
    j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
    %generate 15-minute occupancy data using the Page Algorithm
    Occupancy=occtest(NumberOfBuildings,NumberOfPeople,...
    LongAbsences{j}.averagenumberperyear,...
    LongAbsences{j}.probability,...
    mu,...
    ProbabilityProfiles{j}.probability);
    month=1;
    day=1;
    hour=0;
    % mins=0;
    % sec=0;
    count=1;
    for ii=2:length(Occupancy)

        % create output values for year, month, day, hour and minute if at
        % exact hourly value
        if mod(time(ii),3600)==0; % if we're at an hourly value[1:00, 4:00,
15:00, etc...], this is true!,
            hour=hour+1;
            minute = 0;

            if hour > 24 % if we're at hour 25, we move to the next day,
first hour
                hour=1;
                day=day+1;

                if day > eomday(year, month) %eomday is the ending day of the
month: 31 for jan, mar, 28/29 for feb, 30 for april, etc.
                                            %if we're at day 32 for january,
move to february
                    day=1;
                    month=month+1;

                end

            end

        %create output values for year, month, day, hour and minute if NOT
        %at exact hourly value
```

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```matlab
        else
            %calculate minutes
            if ii == hour*4 + 1;
                minute = 15;
            elseif ii == hour*4 + 2;
                minute = 30;
            else ii == hour*4 + 3;
                minute = 45;
            end

        end %ends 15-minute loop

        % at this point we've established what year, month, day, and
        % hour and minute we are at.

        %within the hourly loop, set values for the occupancy output
        %structure
        occout.year(count)      = year;
        occout.month(count)     = month;
        occout.day(count)       = day;
        occout.hour(count)      = hour;
        occout.minute(count)    = minute;
        occout.val(zone,count)  = Occupancy(ii);

        % [ARTIFACT OF RYAN's MODEL]
        % Now comes the tricky part; how to turn 15-minute data into
        % hourly data? As of this revision, we take the average of
        % occupancy over the last four 15-minute intervals, and round
        % that number up with the 'ceil' command. Then we divide by the
        % total number of people to get a fractional value of total
        % occupancy, (between zero and 1, naturally) which Energyplus
        % can interpret and multiply by an occupant density to get the
        % right number of people.
        % occout.val(zone,count)  = ceil(mean(Occupancy(ii-
3:ii)))/NumberOfPeople;

        if count==35041; %stop when we get to the end of the year
            break
        end

        count=count+1;

    end % of looping through 34041 occupancy entries

end % of zonal loop

OccProfile=occout.val;

end % of function
```

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```
%*************************************************************************
%
%   FUNCTION
%   LightSwitch
%
%   DESCRIPTION
%   Executes manual and automatic portions of Lightswitch 2.0 model
%
%   ARGUMENTS
%
%   OccProfile: Occupancy profile generated by Page code
%
%   OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%   1 in increments of 0.01)
%
%   OffDC: Dampening coefficient for switch-on at departure conditions (0
%   to 1 in increments of 0.01)
%
%   IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%   to 1 in increments of 0.1)
%
%   IntOffDCP: Dampening coefficient for intermediate switch-on conditions
%   (0 to 1 in increments of 0.1)
%
%   RorL: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%   WPE: Average workplane illuminance in 15-minute intervals with blinds
%   retracted
%
%   TargetE: Target illuminance
%
%   LPD: Lighting power density
%
%   ControlSys: Control system type
%
%   DelayTime: Sensor delay time
%
%   BlindControl: Auto or manual control
%
%   OUTPUT
%   Status: On (1) or Off(0) for each 15-minute interval over one year
%
%
%
%   ORIGINAL AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.chinnis@colorado.edu
%
%   NOTES
%
%
%*************************************************************************
function LtgStatus =
LightSwitch(OccProfile,TargetE,n,ControlSys,DelayTime,BlindControl,hourcount,
daycount,BlindStatus)
```

```matlab
%Load overall information
load('ArrOnDC.mat')
load('ArrOnE.mat')
load('ArrOnProb.mat')
load('DepOffDC.mat')
load('DepOffProb.mat')
load('DepOffTime.mat')
load('IntOffDC.mat')
load('IntOffE.mat')
load('IntOffProb.mat')
load('IntOnLDC.mat')
load('IntOnLE.mat')
load('IntOnLProb.mat')
load('IntOnRDC.mat')
load('IntOnRE.mat')
load('IntOnRProb.mat')

%Load run-specific data
load WPE.mat
load RorL.mat
load IntOnDC.mat
load IntOffDCP.mat
load OffDC.mat
load OnDC.mat

hourcount=0;
daycount=0;

%Loop through occupancy data
for k = 2:35041;
%for k = 2:96;

    %identify if occupancy state change happens or doesn't happen
    if OccProfile.val(n,k-1) ~= OccProfile.val(n,k);
        StateChange=1;  %Yes, state change occurs
    else
        StateChange=0;  %No, state change does not occur
    end

    %Figure out if we're at beginning of day
    hourcount=hourcount+.25;
    if hourcount > 24;
        hourcount = 0.25;
        daycount=daycount+1;
    end

    %For each time step, if there is a departure, figure out how
    %long expected absence is
    if OccProfile.val(n,k)==0 && OccProfile.val(n,k-1)==1;
        AbsenceCheck=0;
        for m=k:min((daycount+3)*96,35041);
            if OccProfile.val(n,m)==0;
                AbsenceCheck=AbsenceCheck+1;
            elseif OccProfile.val(n,m) ==1;
                break
            end
```

```matlab
    end
    ExpectedTime=AbsenceCheck*15;
end

%Set initial blind status, OPEN (0) or CLOSED (1)
if hourcount == 0.25;
    BlindStatus(n,k)=0;
%Does space become occupied?
elseif StateChange==1 && OccProfile.val(n,k)==1;
    FirstArrivalTest=0;
    for j = daycount*96+1:k;
        FirstArrivalTest=FirstArrivalTest+OccProfile.val(n,j);
    end
    %If space does become occupied, is it first arrival of the day?
    if FirstArrivalTest==1;
        %If yes, Blinds open blinds
        BlindStatus(n,k)=0;
        %Test is WPE > 2000 LUX?
        if WPE(k,n)>2000;
            %if yes, close blinds
            BlindStatus(n,k)=1;
        else
            %if no, blinds stay open
            BlindStatus(n,k)=0;
        end
    else
        if WPE(k,n)>2000;
            BlindStatus(n,k)=1;
        else
            BlindStatus(n,k)=BlindStatus(n,k-1);
        end
    end
elseif OccProfile.val(n,k)==1;
    %If no, is WPE > 2000 LUX?
    if WPE(k,n)>2000;
        %If yes, close blinds
        BlindStatus(n,k)=1;
    else
        %If no, blinds status stays the same as previous
        BlindStatus(n,k)=BlindStatus(n,k-1);
    end
%If space does not become occupied, then:
else
    %Blind status stays the same as previous


    BlindStatus(n,k)=BlindStatus(n,k-1);
%End blinds routine
end

%Give marker for changing blind status
if BlindStatus(n,k)~= BlindStatus(n,k-1);
    BlindStateChange(n,k)=1;
else
    BlindStateChange(n,k)=0;
end
```

```matlab
    AutoCounter=0;
    %Starting electric lighting status = OFF
    if k == 2;
        LtgStatus(k,n)=0;

    %Was space occupied during last time step?
    elseif OccProfile.val(n,k-1)== 1;
        %If yes, were lights already on?
        if LtgStatus(k-1,n)~= 0;
            %If yes, does occupant leave?
            if StateChange == 1;
                %If Yes and fully manual, stochastic switchoff probability
                if ControlSys == 1 || ControlSys == 4 || ControlSys == 7;
                    %Determine switch-off probability as function of
                    %expected duration of absence
                    DC=OffDC(n);
                    if ExpectedTime > 1440
                        OffProb = 1;
                    else

OffProb=interp2(DepOffDC,DepOffTime,DepOffProb,DC,ExpectedTime);
                    end
                    %Caculate random index
                    OffIndex=rand;
                    %Compare to determined switch-off probability
                    if OffIndex <= OffProb;
                        %Lights switched Off
                        LtgStatus(k,n)=0;
                        %OR, Lights stay On
                    else
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                    end
                %If Yes and fully automatic, check time out and start counter
                else
                    %Lights switched Off
                    if DelayTime <= 15;
                        LtgStatus(k,n)=0;
                    %OR, Lights stay on
                    else
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                        AutoCounter=AutoCounter+1;
                    end
                end
            %If No, stochastic intermediate switch-off
            elseif StateChange == 0;
                %Find intermediate switch-off prob
                if BlindStatus(n,k)==0;
                    Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                else
                    Ill=LtgStatus(k-1,n)*TargetE;
                end
                DC=IntOffDCP(n);
                OffProb=interp2(IntOffDC,IntOffE,IntOffProb,DC,Ill);
                %Pull random number
                IntOffIndex=rand;
```

```matlab
            %Compare to determined intermediate switch-off probability
            if IntOffIndex <= OffProb;
                %Lights switched off
                LtgStatus(k,n)=0;
            else
                %Lights stay at previous state
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
        end
%If spaces was occupied during last time step, but occupant doesn't
%leave
elseif LtgStatus(k-1,n)== 0;
    %If lights were not already on, does occupant leave?
    if StateChange == 1;
        %If Yes, lights remain off
        LtgStatus(k,n)=0;
    %If No, were blinds just adjusted?
    else
        if BlindStateChange(n,k) == 1 && BlindStatus(n,k)==0;
            %If Yes, stochastic switch-on
            %Determine switch-on probability at arrival
            Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
            DC=OnDC(n);
            OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
            %Pull random number
            OnIndex=rand;
            %Compare to determined switch-on probability
            if OnIndex <= OnProb;
                %Lights switched On
                LtgStatus(k,n)=1;
            else
                %Lights stay off
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
        else
            %If No, stochastic intermediate switch-on
            if BlindStatus(n,k)==0;
                Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
            else
                Ill=LtgStatus(k-1,n)*TargetE;
            end
            DC=IntOnDC(n);
            if RorL == 0;
                %Determine switch-on probability (Reinhart & Voss)
                IntOnProb=interp2(IntOnRDC,IntOnRE,IntOnRProb,DC,Ill);
            else
                IntOnProb=interp2(IntOnLDC,IntOnLE,IntOnLProb,DC,Ill);
            end
            %Pull random number
            IntOnIndex=rand;
            %Compare to determine intermediate switch-on probability
            if IntOnIndex <= IntOnProb;
                %Switch On
                LtgStatus(k,n)=1;
            else
                %Stay at previous state
                LtgStatus(k,n)=LtgStatus(k-1,n);
```

```matlab
                    end
                end
            end
        end
    %If space was not already occupied
    elseif OccProfile.val(n,k-1) == 0;
        %If yes, were lights already On?
        if LtgStatus(k-1,n) ~= 0;
            %If Yes, does occupant arrive?
            if OccProfile.val(n,k) == 1;
                if ControlSys == 10 && LtgStatus(k-1,n)==1;
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                elseif ControlSys == 10 && LtgStatus(k-1,n)==0.5;
                    %Stochastic switch-on at arrival for remaining 50%
                    %Determine switch-on probability at arrival
                    Ill=WPE(k,n)+0.5*TargetE;
                    DC=OnDC(n);
                    OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                    %Pull random number
                    OnIndex=rand;
                    %Compare to determined switch-on probability
                    if OnIndex <= OnProb;
                        %Lights switched On
                        LtgStatus(k,n)=1;
                    else
                        %Lights stay off
                        LtgStatus(k,n)=0.5;
                    end
                else
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                end
            else
            %If No, is there an auto-off occ sensor?
                if ControlSys == 2 || ControlSys == 3 || ControlSys == 5 ||
ControlSys == 6 || ControlSys == 8 || ControlSys == 9 || ControlSys == 10;
                    %If yes, has room been unoccupied longer than DT?
                    if AutoCounter*15 >= DelayTime;
                        LtgStatus(k,n)=0;
                    else
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                        AutoCounter=AutoCounter+1;
                    end
                else
                    %If No, lights stay on
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                end
            end
        %If lights were not already On?
        else
            %Does occupant arrive?
            if OccProfile.val(n,k) == 1;
                %If Yes, is there an auto-on occ sensor (all on)?
                if ControlSys == 3 || ControlSys == 6 || ControlSys == 9;
                    %If Yes, lights switched on
                    LtgStatus(k,n)=1;
                elseif ControlSys == 10;
                    %If Yes, 50% switched on automatically, 50% manual
```

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```matlab
                    %Determine switch-on probability at arrival
                    if BlindStatus(n,k)==0;
                        Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                    else
                        Ill=LtgStatus(k-1,n)*TargetE;
                    end
                    Ill=OnDC(n);
                    OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                    %Pull random number
                    OnIndex=rand;
                    %Compare to determined switch-on probability
                    if OnIndex <= OnProb;
                        %Lights switched On
                        LtgStatus(k,n)=1;
                    else
                        %Only 50% switched On (automatically)
                        LtgStatus(k,n)=0.5;
                    end
                else
                    %Stochastic switch-on
                    %Determine switch-on probability at arrival
                    if BlindStatus(n,k)==0;
                        Ill=WPE(k,n)+0.5*TargetE;
                    else
                        Ill=0.5*TargetE;
                    end
                    DC=OnDC(n);
                    OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                    %Pull random number
                    OnIndex=rand;
                    %Compare to determined switch-on probability
                    if OnIndex <= OnProb;
                        %Lights switched On
                        LtgStatus(k,n)=1;
                    else
                        %Lights not switched on
                        LtgStatus(k,n)=0;
                    end
                end
            elseif OccProfile.val(n,k) == 0;
                LtgStatus(k,n)=0;
            end
        end
    %End lightswitch
    end

    %Final status = On (1) or Off (0) for each 15 minute interval over one
    %year

end


end
```

```matlab
%*************************************************************************
%
%   FUNCTION
%   LightSwitchSA
%
%   DESCRIPTION
%   Executes manual and automatic portions of Lightswitch 2.0 model
%   For use with Sensitivity Analysis software (LtgNrgSA and SA)
%
%   ARGUMENTS
%
%   OccProfile: Occupancy profile generated by Page code
%
%   OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%   1 in increments of 0.01)
%
%   OffDC: Dampening coefficient for switch-on at departure conditions (0
%   to 1 in increments of 0.01)
%
%   IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%   to 1 in increments of 0.1)
%
%   IntOffDCP: Dampening coefficient for intermediate switch-on conditions
%   (0 to 1 in increments of 0.1)
%
%   RorL: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%   WPE: Average workplane illuminance in 15-minute intervals with blinds
%   retracted
%
%   TargetE: Target illuminance
%
%   LPD: Lighting power density
%
%   ControlSys: Control system type
%
%   DelayTime: Sensor delay time
%
%   BlindControl: Auto or manual control
%
%   OUTPUT
%   Status: On (1) or Off(0) for each 15-minute interval over one year
%
%
%
%   ORIGINAL AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.oconnor@colorado.edu
%
%   NOTES
%
%
%*************************************************************************
function LtgStatus =
LightSwitchSA(OccProfile,TargetE,n,ControlSys,DelayTime,BlindControl,BlindSta
tus,OnDC,OffDC,IntOffDCP,IntOnDC)
```

```matlab
%Load overall information
load('ArrOnDC.mat')
load('ArrOnE.mat')
load('ArrOnProb.mat')
load('DepOffDC.mat')
load('DepOffProb.mat')
load('DepOffTime.mat')
load('IntOffDC.mat')
load('IntOffE.mat')
load('IntOffProb.mat')
load('IntOnLDC.mat')
load('IntOnLE.mat')
load('IntOnLProb.mat')
load('IntOnRDC.mat')
load('IntOnRE.mat')
load('IntOnRProb.mat')

%Load run-specific data
load WPE.mat
RorL=1;

hourcount=0;
daycount=0;

%Loop through occupancy data
for k = 2:35041;
%for k = 2:96;

    %identify if occupancy state change happens or doesn't happen
    if OccProfile.val(n,k-1) ~= OccProfile.val(n,k);
        StateChange=1;   %Yes, state change occurs
    else
        StateChange=0;   %No, state change does not occur
    end

    %Figure out if we're at beginning of day
    hourcount=hourcount+.25;
    if hourcount > 24;
        hourcount = 0.25;
        daycount=daycount+1;
    end

    %For each time step, if there is a departure, figure out how
    %long expected absence is
    if OccProfile.val(n,k)==0 && OccProfile.val(n,k-1)==1;
        AbsenceCheck=0;
        for m=k:min((daycount+3)*96,35041);
            if OccProfile.val(n,m)==0;
                AbsenceCheck=AbsenceCheck+1;
            elseif OccProfile.val(n,m) ==1;
                break
            end
        end
        ExpectedTime=AbsenceCheck*15;
```

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```
end

%Set initial blind status, OPEN (0) or CLOSED (1)
if hourcount == 0.25;
    BlindStatus(n,k)=0;
%Does space become occupied?
elseif StateChange==1 && OccProfile.val(n,k)==1;
    FirstArrivalTest=0;
    for j = daycount*96+1:k;
        FirstArrivalTest=FirstArrivalTest+OccProfile.val(n,j);
    end
    %If space does become occupied, is it first arrival of the day?
    if FirstArrivalTest==1;
        %If yes, Blinds open blinds
        BlindStatus(n,k)=0;
        %Test is WPE > 2000 LUX?
        if WPE(k,n)>2000;
            %if yes, close blinds
            BlindStatus(n,k)=1;
        else
            %if no, blinds stay open
            BlindStatus(n,k)=0;
        end
    else
        if WPE(k,n)>2000;
            BlindStatus(n,k)=1;
        else
            BlindStatus(n,k)=BlindStatus(n,k-1);
        end
    end
elseif OccProfile.val(n,k)==1;
    %If no, is WPE > 2000 LUX?
    if WPE(k,n)>2000;
        %If yes, close blinds
        BlindStatus(n,k)=1;
    else
        %If no, blinds status stays the same as previous
        BlindStatus(n,k)=BlindStatus(n,k-1);
    end
%If space does not become occupied, then:
else
    %Blind status stays the same as previous


    BlindStatus(n,k)=BlindStatus(n,k-1);
%End blinds routine
end

%Give marker for changing blind status
if BlindStatus(n,k)~= BlindStatus(n,k-1);
    BlindStateChange(n,k)=1;
else
    BlindStateChange(n,k)=0;
end

AutoCounter=0;
```

```matlab
        %Starting electric lighting status = OFF
        if k == 2;
            LtgStatus(k,n)=0;

        %Was space occupied during last time step?
        elseif OccProfile.val(n,k-1)== 1;
            %If yes, were lights already on?
            if LtgStatus(k-1,n)~= 0;
                %If yes, does occupant leave?
                if StateChange == 1;
                    %If Yes and fully manual, stochastic switchoff probability
                    if ControlSys == 1 || ControlSys == 4 || ControlSys == 7;
                        %Determine switch-off probability as function of
                        %expected duration of absence
                        DC=OffDC;
                        if ExpectedTime > 1440
                            OffProb = 1;
                        else

OffProb=interp2(DepOffDC,DepOffTime,DepOffProb,DC,ExpectedTime);
                        end
                        %Caculate random index
                        OffIndex=rand;
                        %Compare to determined switch-off probability
                        if OffIndex <= OffProb;
                            %Lights switched Off
                            LtgStatus(k,n)=0;
                            %OR, Lights stay On
                        else
                            LtgStatus(k,n)=LtgStatus(k-1,n);
                        end
                    %If Yes and fully automatic, check time out and start counter
                    else
                        %Lights switched Off
                        if DelayTime <= 15;
                            LtgStatus(k,n)=0;
                        %OR, Lights stay on
                        else
                            LtgStatus(k,n)=LtgStatus(k-1,n);
                            AutoCounter=AutoCounter+1;
                        end
                    end
                %If No, stochastic intermediate switch-off
                elseif StateChange == 0;
                    %Find intermediate switch-off prob
                    if BlindStatus(n,k)==0;
                        Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                    else
                        Ill=LtgStatus(k-1,n)*TargetE;
                    end
                    DC=IntOffDCP;
                    OffProb=interp2(IntOffDC,IntOffE,IntOffProb,DC,Ill);
                    %Pull random number
                    IntOffIndex=rand;
                    %Compare to determined intermediate switch-off probability
                    if IntOffIndex <= OffProb;
                        %Lights switched off
```
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```matlab
                LtgStatus(k,n)=0;
            else
                %Lights stay at previous state
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
        end
    %If spaces was occupied during last time step, but occupant doesn't
    %leave
    elseif LtgStatus(k-1,n)== 0;
        %If lights were not already on, does occupant leave?
        if StateChange == 1;
            %If Yes, lights remain off
            LtgStatus(k,n)=0;
        %If No, were blinds just adjusted?
        else
            if BlindStateChange(n,k) == 1 && BlindStatus(n,k)==0;
                %If Yes, stochastic switch-on
                %Determine switch-on probability at arrival
                Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                DC=OnDC;
                OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                %Pull random number
                OnIndex=rand;
                %Compare to determined switch-on probability
                if OnIndex <= OnProb;
                    %Lights switched On
                    LtgStatus(k,n)=1;
                else
                    %Lights stay off
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                end
            else
                %If No, stochastic intermediate switch-on
                if BlindStatus(n,k)==0;
                    Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                else
                    Ill=LtgStatus(k-1,n)*TargetE;
                end
                DC=IntOnDC;
                if RorL == 0;
                    %Determine switch-on probability (Reinhart & Voss)
                    IntOnProb=interp2(IntOnRDC,IntOnRE,IntOnRProb,DC,Ill);
                else
                    IntOnProb=interp2(IntOnLDC,IntOnLE,IntOnLProb,DC,Ill);
                end
                %Pull random number
                IntOnIndex=rand;
                %Compare to determine intermediate switch-on probability
                if IntOnIndex <= IntOnProb;
                    %Switch On
                    LtgStatus(k,n)=1;
                else
                    %Stay at previous state
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                end
            end
        end
```

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```
            end
        %If space was not already occupied
        elseif OccProfile.val(n,k-1) == 0;
            %If yes, were lights already On?
            if LtgStatus(k-1,n) ~= 0;
                %If Yes, does occupant arrive?
                if OccProfile.val(n,k) == 1;
                    if ControlSys == 10 && LtgStatus(k-1,n)==1;
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                    elseif ControlSys == 10 && LtgStatus(k-1,n)==0.5;
                        %Stochastic switch-on at arrival for remaining 50%
                        %Determine switch-on probability at arrival
                        Ill=WPE(k,n)+0.5*TargetE;
                        DC=OnDC;
                        OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                        %Pull random number
                        OnIndex=rand;
                        %Compare to determined switch-on probability
                        if OnIndex <= OnProb;
                            %Lights switched On
                            LtgStatus(k,n)=1;
                        else
                            %Lights stay off
                            LtgStatus(k,n)=0.5;
                        end
                    else
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                    end
                else
                %If No, is there an auto-off occ sensor?
                    if ControlSys == 2 || ControlSys == 3 || ControlSys == 5 ||
ControlSys == 6 || ControlSys == 8 || ControlSys == 9 || ControlSys == 10;
                        %If yes, has room been unoccupied longer than DT?
                        if AutoCounter*15 >= DelayTime;
                            LtgStatus(k,n)=0;
                        else
                            LtgStatus(k,n)=LtgStatus(k-1,n);
                            AutoCounter=AutoCounter+1;
                        end
                    else
                        %If No, lights stay on
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                    end
                end
            %If lights were not already On?
            else
                %Does occupant arrive?
                if OccProfile.val(n,k) == 1;
                    %If Yes, is there an auto-on occ sensor (all on)?
                    if ControlSys == 3 || ControlSys == 6 || ControlSys == 9;
                        %If Yes, lights switched on
                        LtgStatus(k,n)=1;
                    elseif ControlSys == 10;
                        %If Yes, 50% switched on automatically, 50% manual
                        %Determine switch-on probability at arrival
                        if BlindStatus(n,k)==0;
                            Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
```

```matlab
                else
                    Ill=LtgStatus(k-1,n)*TargetE;
                end
                Ill=OnDC;
                OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                %Pull random number
                OnIndex=rand;
                %Compare to determined switch-on probability
                if OnIndex <= OnProb;
                    %Lights switched On
                    LtgStatus(k,n)=1;
                else
                    %Only 50% switched On (automatically)
                    LtgStatus(k,n)=0.5;
                end
            else
                %Stochastic switch-on
                %Determine switch-on probability at arrival
                if BlindStatus(n,k)==0;
                    Ill=WPE(k,n)+0.5*TargetE;
                else
                    Ill=0.5*TargetE;
                end
                DC=OnDC;
                OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                %Pull random number
                OnIndex=rand;
                %Compare to determined switch-on probability
                if OnIndex <= OnProb;
                    %Lights switched On
                    LtgStatus(k,n)=1;
                else
                    %Lights not switched on
                    LtgStatus(k,n)=0;
                end
            end
        elseif OccProfile.val(n,k) == 0;
            LtgStatus(k,n)=0;
        end
    end
%End lightswitch
end

%Final status = On (1) or Off (0) for each 15 minute interval over one
%year


end


end
```

```
%**************************************************************************
%
%   FUNCTION
%   LightSwitchVAL
%
%   DESCRIPTION
%   Executes manual and automatic portions of Lightswitch 2.0 model
%   For use with Validation software (LtgNrgVAL)
%
%   ARGUMENTS
%
%   OccProfile: Occupancy profile generated by Page code
%
%   OnDC: Dampening coefficient for switch-on at arrival conditions (0 to
%   1 in increments of 0.01)
%
%   OffDC: Dampening coefficient for switch-on at departure conditions (0
%   to 1 in increments of 0.01)
%
%   IntOnDC: Dampening coefficient for intermediate switch-on conditions (0
%   to 1 in increments of 0.1)
%
%   IntOffDCP: Dampening coefficient for intermediate switch-on conditions
%   (0 to 1 in increments of 0.1)
%
%   RorL: 0 for Reinhart & Voss curve, 1 for Lindelof curve
%
%   WPE: Average workplane illuminance in 15-minute intervals with blinds
%   retracted
%
%   TargetE: Target illuminance
%
%   LPD: Lighting power density
%
%   ControlSys: Control system type
%
%   DelayTime: Sensor delay time
%
%   BlindControl: Auto or manual control
%
%   OUTPUT
%   Status: On (1) or Off(0) for each 15-minute interval over one year
%
%
%
%   ORIGINAL AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.oconnor@colorado.edu
%
%   NOTES
%
%
%**************************************************************************
function LtgStatus =
LightSwitch(OccProfile,TargetE,n,ControlSys,DelayTime,BlindControl,hourcount,
daycount,BlindStatus,OnDC,OffDC,IntOnDC,IntOffDCP,RorL)
```

```matlab
%Load overall information
load('ArrOnDC.mat')
load('ArrOnE.mat')
load('ArrOnProb.mat')
load('DepOffDC.mat')
load('DepOffProb.mat')
load('DepOffTime.mat')
load('IntOffDC.mat')
load('IntOffE.mat')
load('IntOffProb.mat')
load('IntOnLDC.mat')
load('IntOnLE.mat')
load('IntOnLProb.mat')
load('IntOnRDC.mat')
load('IntOnRE.mat')
load('IntOnRProb.mat')

%Load run-specific data
load WPE_DLTest.mat
%load RorL.mat
%load IntOnDC.mat
%load IntOffDCP.mat
%load OffDC.mat
%load OnDC.mat

hourcount=0;
daycount=0;

%Loop through occupancy data
for k = 2:35041;
%for k = 2:96;

    %identify if occupancy state change happens or doesn't happen
    if OccProfile.val(n,k-1) ~= OccProfile.val(n,k);
        StateChange=1;  %Yes, state change occurs
    else
        StateChange=0;  %No, state change does not occur
    end

    %Figure out if we're at beginning of day
    hourcount=hourcount+.25;
    if hourcount > 24;
        hourcount = 0.25;
        daycount=daycount+1;
    end

    %For each time step, if there is a departure, figure out how
    %long expected absence is
    if OccProfile.val(n,k)==0 && OccProfile.val(n,k-1)==1;
        AbsenceCheck=0;
        for m=k:min((daycount+3)*96,35041);
            if OccProfile.val(n,m)==0;
                AbsenceCheck=AbsenceCheck+1;
            elseif OccProfile.val(n,m) ==1;
```

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```
            break
        end
    end
    ExpectedTime=AbsenceCheck*15;
end

%Set initial blind status, OPEN (0) or CLOSED (1)
if hourcount == 0.25;
    BlindStatus(n,k)=0;
%Does space become occupied?
elseif StateChange==1 && OccProfile.val(n,k)==1;
    FirstArrivalTest=0;
    for j = daycount*96+1:k;
        FirstArrivalTest=FirstArrivalTest+OccProfile.val(n,j);
    end
    %If space does become occupied, is it first arrival of the day?
    if FirstArrivalTest==1;
        %If yes, Blinds open blinds
        BlindStatus(n,k)=0;
        %Test is WPE > 2000 LUX?
        if WPE(k,n)>2000;
            %if yes, close blinds
            BlindStatus(n,k)=1;
        else
            %if no, blinds stay open
            BlindStatus(n,k)=0;
        end
    else
        if WPE(k,n)>2000;
            BlindStatus(n,k)=1;
        else
            BlindStatus(n,k)=BlindStatus(n,k-1);
        end
    end
elseif OccProfile.val(n,k)==1;
    %If no, is WPE > 2000 LUX?
    if WPE(k,n)>2000;
        %If yes, close blinds
        BlindStatus(n,k)=1;
    else
        %If no, blinds status stays the same as previous
        BlindStatus(n,k)=BlindStatus(n,k-1);
    end
%If space does not become occupied, then:
else
    %Blind status stays the same as previous


    BlindStatus(n,k)=BlindStatus(n,k-1);
%End blinds routine
end

%Give marker for changing blind status
if BlindStatus(n,k)~= BlindStatus(n,k-1);
    BlindStateChange(n,k)=1;
else
```

```matlab
        BlindStateChange(n,k)=0;
    end

    AutoCounter=0;
    %Starting electric lighting status = OFF
    if k == 2;
        LtgStatus(k,n)=0;

    %Was space occupied during last time step?
    elseif OccProfile.val(n,k-1)== 1;
        %If yes, were lights already on?
        if LtgStatus(k-1,n)~= 0;
            %If yes, does occupant leave?
            if StateChange == 1;
                %If Yes and fully manual, stochastic switchoff probability
                if ControlSys == 1 || ControlSys == 4 || ControlSys == 7;
                    %Determine switch-off probability as function of
                    %expected duration of absence
                    DC=OffDC(n);
                    if ExpectedTime > 1440
                        OffProb = 1;
                    else

OffProb=interp2(DepOffDC,DepOffTime,DepOffProb,DC,ExpectedTime);
                    end
                    %Caculate random index
                    OffIndex=rand;
                    %Compare to determined switch-off probability
                    if OffIndex <= OffProb;
                        %Lights switched Off
                        LtgStatus(k,n)=0;
                        %OR, Lights stay On
                    else
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                    end
                %If Yes and fully automatic, check time out and start counter
                else
                    %Lights switched Off
                    if DelayTime <= 15;
                        LtgStatus(k,n)=0;
                    %OR, Lights stay on
                    else
                        LtgStatus(k,n)=LtgStatus(k-1,n);
                        AutoCounter=AutoCounter+1;
                    end
                end
            %If No, stochastic intermediate switch-off
            elseif StateChange == 0;
                %Find intermediate switch-off prob
                if BlindStatus(n,k)==0;
                    Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                else
                    Ill=LtgStatus(k-1,n)*TargetE;
                end
                DC=IntOffDCP(n);
                OffProb=interp2(IntOffDC,IntOffE,IntOffProb,DC,Ill);
```

```matlab
            %Pull random number
            IntOffIndex=rand;
            %Compare to determined intermediate switch-off probability
            if IntOffIndex <= OffProb;
                %Lights switched off
                LtgStatus(k,n)=0;
            else
                %Lights stay at previous state
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
    end
%If spaces was occupied during last time step, but occupant doesn't
%leave
elseif LtgStatus(k-1,n)== 0;
    %If lights were not already on, does occupant leave?
    if StateChange == 1;
        %If Yes, lights remain off
        LtgStatus(k,n)=0;
    %If No, were blinds just adjusted?
    else
        if BlindStateChange(n,k) == 1 && BlindStatus(n,k)==0;
            %If Yes, stochastic switch-on
            %Determine switch-on probability at arrival
            Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
            DC=OnDC(n);
            OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
            %Pull random number
            OnIndex=rand;
            %Compare to determined switch-on probability
            if OnIndex <= OnProb;
                %Lights switched On
                LtgStatus(k,n)=1;
            else
                %Lights stay off
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
        else
            %If No, stochastic intermediate switch-on
            if BlindStatus(n,k)==0;
                Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
            else
                Ill=LtgStatus(k-1,n)*TargetE;
            end
            DC=IntOnDC(n);
            if RorL == 0;
                %Determine switch-on probability (Reinhart & Voss)
                IntOnProb=interp2(IntOnRDC,IntOnRE,IntOnRProb,DC,Ill);
            else
                IntOnProb=interp2(IntOnLDC,IntOnLE,IntOnLProb,DC,Ill);
            end
            %Pull random number
            IntOnIndex=rand;
            %Compare to determine intermediate switch-on probability
            if IntOnIndex <= IntOnProb;
                %Switch On
                LtgStatus(k,n)=1;
            else
```

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```matlab
                    %Stay at previous state
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                end
            end
        end
    end
%If space was not already occupied
elseif OccProfile.val(n,k-1) == 0;
    %If yes, were lights already On?
    if LtgStatus(k-1,n) ~= 0;
        %If Yes, does occupant arrive?
        if OccProfile.val(n,k) == 1;
            if ControlSys == 10 && LtgStatus(k-1,n)==1;
                LtgStatus(k,n)=LtgStatus(k-1,n);
            elseif ControlSys == 10 && LtgStatus(k-1,n)==0.5;
                %Stochastic switch-on at arrival for remaining 50%
                %Determine switch-on probability at arrival
                Ill=WPE(k,n)+0.5*TargetE;
                DC=OnDC(n);
                OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                %Pull random number
                OnIndex=rand;
                %Compare to determined switch-on probability
                if OnIndex <= OnProb;
                    %Lights switched On
                    LtgStatus(k,n)=1;
                else
                    %Lights stay off
                    LtgStatus(k,n)=0.5;
                end
            else
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
        else
        %If No, is there an auto-off occ sensor?
            if ControlSys == 2 || ControlSys == 3 || ControlSys == 5 ||
ControlSys == 6 || ControlSys == 8 || ControlSys == 9 || ControlSys == 10;
                %If yes, has room been unoccupied longer than DT?
                if AutoCounter*15 >= DelayTime;
                    LtgStatus(k,n)=0;
                else
                    LtgStatus(k,n)=LtgStatus(k-1,n);
                    AutoCounter=AutoCounter+1;
                end
            else
                %If No, lights stay on
                LtgStatus(k,n)=LtgStatus(k-1,n);
            end
        end
    %If lights were not already On?
    else
        %Does occupant arrive?
        if OccProfile.val(n,k) == 1;
            %If Yes, is there an auto-on occ sensor (all on)?
            if ControlSys == 3 || ControlSys == 6 || ControlSys == 9;
                %If Yes, lights switched on
                LtgStatus(k,n)=1;
```

```matlab
            elseif ControlSys == 10;
                %If Yes, 50% switched on automatically, 50% manual
                %Determine switch-on probability at arrival
                if BlindStatus(n,k)==0;
                    Ill=WPE(k,n)+LtgStatus(k-1,n)*TargetE;
                else
                    Ill=LtgStatus(k-1,n)*TargetE;
                end
                Ill=OnDC(n);
                OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                %Pull random number
                OnIndex=rand;
                %Compare to determined switch-on probability
                if OnIndex <= OnProb;
                    %Lights switched On
                    LtgStatus(k,n)=1;
                else
                    %Only 50% switched On (automatically)
                    LtgStatus(k,n)=0.5;
                end
            else
                %Stochastic switch-on
                %Determine switch-on probability at arrival
                if BlindStatus(n,k)==0;
                    Ill=WPE(k,n)+0.5*TargetE;
                else
                    Ill=0.5*TargetE;
                end
                DC=OnDC(n);
                OnProb=interp2(ArrOnDC,ArrOnE,ArrOnProb,DC,Ill);
                %Pull random number
                OnIndex=rand;
                %Compare to determined switch-on probability
                if OnIndex <= OnProb;
                    %Lights switched On
                    LtgStatus(k,n)=1;
                else
                    %Lights not switched on
                    LtgStatus(k,n)=0;
                end
            end
        elseif OccProfile.val(n,k) == 0;
            LtgStatus(k,n)=0;
        end
    end
    %End lightswitch
    end

    %Final status = On (1) or Off (0) for each 15 minute interval over one
    %year

end


end
```

```
%*************************************************************************
%
%    FUNCTION
%    ConvTest
%
%    DESCRIPTION
%    Executes combined LightSwitchConv 2000 times to gather energy data for
%    convergence tewsting
%
%    ARGUMENTS
%    none
%
%    OUTPUT
%    Annual energy density for 2000 simulations
%
%    ORIGINAL AUTHOR
%    Darcie Chinnis
%    University of Colorado
%    darcie.oconnor@colorado.edu
%
%    NOTES
%
%
%*************************************************************************

function values=ConvTest()

values(1:2000,1)=0;

for a = 1:2000;

    values(a,1)=LtgNrgConv();

end
```

```matlab
function [occCumul,histoAbsTimes,histoAbsFreq,histoAbsAver,...
    histoOccTimes,histoOccFreq,histoOccAver]=...
    occmodel(t,occInit,occMax,shuff,probHour,...
    nAbsAver,absDurationProb,absDurationBin,absDurationMin,...
    firstDay,histoFlag,histoAbsBin,histoAbsNBin,histoOccBin,histoOccNBin)
% calculation of cumulated effective occupancy
% for occMax persons, for the times given in the nt array
% version 1.4: add absence blocks

% Parameters:
% - t               = array of times for which occupancy will be calculated
[s]
% - occInit         = initial value of occupancy (0 or 1)
% - occMax          = number of persons
% - shuff           = shuffling parameter
% - probHour        = array of hourly occupancy probability profiles
% - nAbsAver        = average number of absences during one year
% - absDurationProb = array of absence duration probability
% - absDurationBin  = absence duration probability bin [hours]
% - absDurationMin  = absence duration minimum [hours]
% - firstDay        = first day of the year (1=Monday, 2=Tuesday, ...
7=Sunday)
% - histoFlag       = occupancy histogram (0=no histogram, 1=per day, 2=per
week)
% - histoAbsBin     = absence duration histogram bin [hours]
% - histoAbsNBin    = absence duration histogram number of bins
% - histoOccBin     = occupancy histogram bin [hours]
% - histoOccNBin    = occupancy histogram number of bins
% Outputs:
% - occCumul        = cumulated occupancy corresponding to the t array
% - histoAbsTimes   = times for the block absence histogram [hours]
% - histoAbsFreq    = values (frequencies) for the block absence histogram
% - histoAbsAver    = average block absence time [hours]
% - histoOccTimes   = times for the daily occupancy histogram [hours]
% - histoOccFreq    = values (frequencies) for the daily/weekly occupancy
histogram
% - histoOccAver    = average of daily/weekly occupancy time
%
% The first output argument is mandatory; all the others are optional,
% but they should be either all present or all absent; they should
% be present if histoFlag>0
%
% For each person, an independent occupancy
% profile is drawn at random, using the
% transition probability time arrays T01 and T11

% indexes:
% index1(k=1 to nprobHour)=pointer to plist element corresponding to
% the hourly profile element k (value: 1 to nplist)
% index2(i=1 to nt)=pointer to plist element corresponding to the
% time step i (value: 1 to nplist)

% check number of input and output arguments
if (nargin~=10 & nargin~=15)
    error('*** occrandom1 error: nargin = %i, should be 10 or 15',nargin)
end
```

```
if (nargout~=1 & nargout~=7)
    error('*** occrandom1 error: nargin = %i, should be 1 or 7',nargout)
end
if (histoFlag>0 & nargout~=7)
    error('*** occrandom1 error: nargin = %i, should be 7 because
histoFlag>0',nargout)
end
%% RT1
% calculate the possible occupancy probabilities
% it is supposed that the maximum number of different
% occupancy probability values is PMAX = 10
% (if larger, the function stops with an error message)
% % % % % nprobHour=length(probHour);
% % % % % index1=zeros(1,nprobHour);
% % % % % NPMAX=4*24*7;
% % % % % plist=zeros(1,NPMAX);
% % % % % nplist=1; plist(1)=0; index1(1)=1; % first element = zero occupancy
probability
% % % % % for k=1:nprobHour,
% % % % %     pfound=find(probHour(k)==plist(1:nplist));
% % % % %     if (length(pfound)==0),
% % % % %         % found new probability value
% % % % %         if (nplist<NPMAX),
% % % % %             nplist=nplist+1; plist(nplist)=probHour(k);
index1(k)=nplist;
% % % % %         else
% % % % %             error('*** occrandom1 error: more than %i probability
values',NPMAX)
% % % % %         end
% % % % %     else
% % % % %         % already existing probability value
% % % % %         index1(k)=pfound(1);
% % % % %     end
% % % % % end
% % % % %
% % % % % % calculate transition probability matrices T01 and T11
% % % % % T01list=zeros(NPMAX,NPMAX);
% % % % % T11list=zeros(NPMAX,NPMAX);
% % % % % for j1=1:NPMAX,
% % % % %     for j2=1:NPMAX,
% % % % %
[T01list(j1,j2),T11list(j1,j2)]=occtrans1(plist(j1),plist(j2),shuff);
% % % % %     end
% % % % % end
%% RT2 ============================BEGIN MAIN CODE========================
T01List=zeros(1,length(probHour));
T11List=zeros(1,length(probHour));
for j=1:length(probHour)-1
    [T01List(j),T11List(j)]=occtrans1(probHour(j),probHour(j+1),shuff);
end

% calculate occupancy probability time arrays
nt=length(t);
dt=t(2)-t(1);
daynb=zeros(1,nt);
weeknb=zeros(1,nt);
index2=zeros(1,nt); % for each timestep, index in the plist array
```

```
pBlockAbs=nAbsAver/nt; % probability of starting a block absence at each
timestep

for i=1:nt,
    tday=mod(t(i),86400); % time in the day
    daynb(i)=fix(t(i)/86400); % day number in the year
    weeknb(i)=fix((daynb(i)+firstDay+5)/7); % week number in the year (1 to
53)
    h=fix(tday/3600); % full hour in the day
    m=month1(daynb(i)); % month number (1 to 12)
    weekday=mod(daynb(i)+firstDay-2,7)+1; % day of the week (1 to 7)
    if (weekday==6) w=2; % Saturday
    elseif (weekday==7) w=3; % Sunday
    else w=1; end % weekday
    k=h+1+24*(w-1)+3*24*(m-1); % index in the probHour array
%    index2(i)=index1(k); % index in the plist array
end

% time distribution of block absence: calculate cumulative distribution
% function and prepare histogram
nabs=length(absDurationProb);
absDurationProbCumul=cumsum(absDurationProb); % cumulative probability
if (abs(absDurationProbCumul(nabs)-1)>nabs*eps)
    error('*** occrandom1 error: absDurationProbCumul(%i) = %f, should be
1',nabs,absDurationProbCumul(nabs))
end
% preparing bins for the distribution of periods of long absence
if (histoFlag>0)
    hmax=histoAbsBin*(histoAbsNBin-1); % value for the beginning of last bin
    histoAbsTimes=[0:histoAbsBin:hmax];
    histoAbsFreq=zeros(1,histoAbsNBin);
    histoAbsAver=0;
    histoAbsTot=0;
end

% time distribution of daily/weekly occupancy: prepare histogram
if (histoFlag>0)
    hmax=histoOccBin*(histoOccNBin-1); % value for the beginning of last bin
    histoOccTimes=[0:histoOccBin:hmax];
    histoOccFreq=zeros(1,histoOccNBin);
    histoOccAver=0;
    histoOccTot=0;
end

% calculate occupancy simulated by the stochastic model
occCumul=zeros(1,nt);
for k=1:occMax
    occ0=occInit; % initial value of occupancy
    blockAbs0=0; % initial value of block absence: 0 (normal occupancy)
    occCumul(1)=occCumul(1)+occ0;
    occtime=0; % initial value of daily/weekly occupation time [hours]
    if (histoFlag==1) daynb0=daynb(1); end
    if (histoFlag==2) weeknb0=weeknb(1); end
    for i=1:nt-1
        % if nargout>1 and day/week has changed, increment the daily/weekly
occupation histogram
```

```matlab
            if (histoFlag==1 & daynb(i)>daynb0)
                j=fix(occtime/histoOccBin)+1;
                if (j>=1 & j<=histoOccNBin)
                    histoOccFreq(j)=histoOccFreq(j)+1;
                end
                histoOccAver=histoOccAver+occtime; histoOccTot=histoOccTot+1;
                daynb0=daynb(i);
                occtime=0;
            elseif (histoFlag==2 & weeknb(i)>weeknb0)
                j=fix(occtime/histoOccBin)+1;
                if (j>=1 & j<=histoOccNBin)
                    histoOccFreq(j)=histoOccFreq(j)+1;
                end
                histoOccAver=histoOccAver+occtime; histoOccTot=histoOccTot+1;
                weeknb0=weeknb(i);
                occtime=0;
            end
            % determine whether a block absence should start
            if (blockAbs0==0) % currently not in a block absence
                x=rand(1);
                if (x<pBlockAbs)
                    blockAbs=1; % start a block absence
                    % determine the duration of block absence
                    x=rand(1);
                    g=find(absDurationProbCumul<x);
                    x=rand(1);
                    dBlockAbs=(length(g)+x)*absDurationBin+absDurationMin;
%hours, minimum absDurationMin
                    tEndBlockAbs=t(i)+dBlockAbs*3600;
                    if (histoFlag>0)
                        j=fix(dBlockAbs/absDurationBin)+1;
                        if (j>=1 & j<=histoAbsNBin)
                            histoAbsFreq(j)=histoAbsFreq(j)+1;
                        end
                        histoAbsAver=histoAbsAver+dBlockAbs;
                    end
                else
                    blockAbs=0;
                end
            else % currently in a block absence, check possible end
                if (t(i)>tEndBlockAbs)
                    blockAbs=0;
                else
                    blockAbs=1;
                end
            end
% % % % %           if (blockAbs0==0), j1=index2(i);
% % % % %           else j1=1; end
% % % % %           if (blockAbs==0), j2=index2(i+1);
% % % % %           else j2=1; end
% % % % %           T01=T01list(j1,j2);
% % % % %           T11=T11list(j1,j2);
            if (blockAbs==1) % occupant just left on long absence
                occ=0;
            elseif (blockAbs0==1)&&(blockAbs==0) % occupant just came back from
long absence
                occ=1;
```

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```matlab
        else
            T01=T01List(mod(i-1,672)+1);
            T11=T11List(mod(i-1,672)+1);
            x=rand(1);
            if (occ0==0) % room currently not occupied
                if (T01>x)
                    occ=1;
                else
                    occ=0;
                end
            elseif (occ0==1) % room currently occupied
                T10=1-T11;
                if (T10>x)
                    occ=0;
                else
                    occ=1;
                end
            end
        end
        occ0=occ;
        blockAbs0=blockAbs;
        occCumul(i+1)=occCumul(i+1)+occ;
        if (histoFlag>0)
            occtime=occtime+dt*occ/3600;
        end
    end % loop through time period  *RT
end % loop for each occupant  *RT


% average values
if (histoFlag>0),
    if (histoAbsTot>0),
        histoAbsAver=histoAbsAver/histoAbsTot;
    end
    if (histoOccTot>0),
        histoOccAver=histoOccAver/histoOccTot;
    end
end


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%


function m=month1(daynb)
% calculate month number (1 to 12) corresponding to daynb
% (number of day in the year, from 1 to 365)
% current version: no leap year !

firstday=[1,32,60,91,121,152,182,213,244,274,305,335,9999];
m1=find(daynb<firstday);
m=m1(1)-1;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
```

```matlab
function [T01,T11]=occtrans1(pcurr,pnext,shuff)
% calculation of transition probability, model 1
% T01=probability of transition 0 -> 1
% T11=probability of transition 1 -> 1
% (note: T00=1-T01, T10=1-T11)
% pcurr=current step occupancy probability
% pnext=next step occupancy probability
% shuff = shuffling parameter
% beta = adjusted value of shuff

beta=shuff; % default: no adjustment needed

if(pnext==0)
    T01=0;
    T11=0;
elseif(pnext==1)
    T01=1;
    T11=1;
else
    if (pcurr==1)
        T11=pnext;
        T01=0;
    elseif (pcurr==0)
        T01=pnext;
        T11=0;
    elseif (pcurr==pnext)
        if (pcurr+pnext>1)
            if (shuff>1/(2*pcurr-1))
                beta=1/(2*pcurr-1);
            else
                beta=shuff;
            end
        elseif (pcurr+pnext<1)
            if (shuff>1/(1-2*pcurr))
                beta=1/(1-2*pcurr);
            else
                beta=shuff;
            end
        else
            beta=shuff;
        end
        T01=2*beta*pcurr/(beta+1);
        T11=1-(1-pcurr)*T01/pcurr;
    elseif (pcurr<pnext)
        if (shuff<(pnext-pcurr)/(2-(pnext+pcurr)))
            beta=(pnext-pcurr)/(2-(pnext+pcurr));
        else
            if ((pcurr+pnext>1) & (shuff>(pcurr-pnext+1)/(pnext+pcurr-1)))
                beta=(pcurr-pnext+1)/(pnext+pcurr-1);
            elseif ((pcurr+pnext<1) & (shuff>(1-pcurr+pnext)/(1-pcurr-
pnext)))
                beta=(1-pcurr+pnext)/(1-pcurr-pnext);
            else
                beta=shuff;
            end
```

```
        end
        T01=pnext+pcurr*(beta-1)/(beta+1);
        T11=1/pcurr*(pnext-(1-pcurr)*T01);
    else % (pcurr>pnext)
        if (shuff<(pcurr-pnext)/(pnext+pcurr))
            beta=(pcurr-pnext)/(pnext+pcurr);
        else
            if ((pcurr+pnext>1) & (shuff>(pcurr-pnext+1)/(pnext+pcurr-1)))
                beta=(pcurr-pnext+1)/(pnext+pcurr-1);
            elseif ((pcurr+pnext<1) & (shuff>(1-pcurr+pnext)/(1-pcurr-
pnext)))
                beta=(1-pcurr+pnext)/(1-pcurr-pnext);
            else
                beta=shuff;
            end
        end
        T01=pnext+pcurr*(beta-1)/(beta+1);
        T11=1/pcurr*(pnext-(1-pcurr)*T01);
    end
end

% print a message if shuff and beta are not equal
% if (beta~=shuff)
%     fprintf('***Warning: the shuffling parameters had to be adjusted\n');
%     fprintf('           pcurr=%6.2f, pnext=%6.2f, shuff=%6.2f adjusted to
%6.2f\n',...
%         pcurr,pnext,shuff,beta)
% end
```

```matlab
function[occCumul,histoOccTimes,histoOccFreq,histoOccAver,histoAbsTimes,...
    histoAbsFreq,histoAbsAver]= occtest(NumberOfBuildings,NumberOfPeople,...
                            AverageNumberofLongAbsences,...
                            LongAbsenceProbabilityDistribution,...
                            MuParameter,...
                            ProbabilityProfile)
% histoAbsAver,
% histoOccAver,
% histoAbsTimes/24,histoAbsFreq,
% histoOccTimes,histoOccFreq,

% script occupancy model 1.4 (now it's a function so I can enter my
parameters easily)
% generation of an occupancy profile
% occMax=maximum number of persons in the zone
% tmin=minimum generation time [s]
% tmax=maximum generation time [s]
% dt=calculation timestep [s]
% [t1,t2]=morning occupancy interval [s]
% [t3,t4]=afternoon occupancy interval [s]
% p1=occupancy probability for t<t1 or t>t4, or week-end
% p2=occupancy probability for [t1,t2]
% p3=occupancy probability for [t2,t3]
% p4=occupancy probability for [t3,t4]
% shuff=shuffling parameter

nb=NumberOfBuildings; % number of buildings
occMaxBuilding=NumberOfPeople; % max occupancy for each building
occMaxTot=occMaxBuilding*nb;
tmin=1*86400;
tmax=(1*365+1)*86400;
dt=900;
shuff=MuParameter;
nAbsAver=AverageNumberofLongAbsences; % average number of block absences
during the considered period
absDurationProb=LongAbsenceProbabilityDistribution; % block absence
probabilities
absDurationBin=12; % bin for the block absence probability [hours]
absDurationMin=12; % minimum block absence duration [hours]
histoAbsBin=6; % absence histogram bin [hours]
histoAbsNBin=100; % absence histogram number of bins
histoOccBin= 1/4; % daily/weekly occupancy histogram bin [quarters of an
hour]
histoOccNBin=100*4; % daily/weekly occupancy histogram number of bins

% generation of time array and initialization
t=[tmin:dt:tmax]; nt=length(t); % nt = number of time steps
occ0=0; % initial value: room supposed to be unoccupied
occCumul=zeros(size(t));
firstDay=1; % arbitrary value (Monday)

% options
optionBuilding=1; % 1=all buildings together, 2=each building separately
optionHisto=2; % 0=no histogram, 1=daily occupancy histogram, 2=weekly
occupancy histogram
```

```matlab
% calculate occupancy probability array, hour by hour:
% for each month, 3 daily profiles (24 values) for
% Mondays to Fridays, Saturdays, Sundays
% --> altogether 12 * 3 * 24 = 864 values
tic;
%probhour=probhour_Office003(WeekdayHourlyProbProfile,SaturdayHourlyProbProfi
le,SundayHourlyProbProfile);
probhour=ProbabilityProfile;
cpu1=toc;
if (optionBuilding==1),
    % calculate occupancy simulated by stochastic model
    % optionBuilding==1: all buildings calculated at once, only one function
call
    tic;
    if (optionHisto==0),
        occCumul=...
            occmodel(t,occ0,occMaxTot,shuff,probhour,nAbsAver,...

absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto);
    elseif (optionHisto>0),
        [occCumul,histoAbsTimes,histoAbsFreq,histoAbsAver,...
            histoOccTimes,histoOccFreq,histoOccAver]=...
            occmodel(t,occ0,occMaxTot,shuff,probhour,nAbsAver,...

absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto,...
            histoAbsBin,histoAbsNBin,histoOccBin,histoOccNBin);
    end
    cpu2=toc;
elseif (optionBuilding==2),
    % calculated occupancy simulated by stochastic model
    % optionBuilding==2: every building calculated with a different profile,
nb function calls
    tic;
    for i=1:nb % loop on buildings
        if (optionHisto==0),
            occBuilding=...
                occmodel(t,occ0,occMaxBuilding,shuff,probhour,nAbsAver,...

absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto);
        elseif (optionHisto>0),

[occBuilding,histoAbsTimes,histoAbsFreqBuilding,histoAbsAverBuilding,....
                histoOccTimes,histoOccFreqBuilding,histoOccAverBuilding]=...
                occmodel(t,occ0,occMaxBuilding,shuff,probhour,...

nAbsAver,absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto,.
..
                histoAbsBin,histoAbsNBin,histoOccBin,histoOccNBin);
        end
        if (i==1)
            occCumul=zeros(size(t));
            if (optionHisto>0),
                histoAbsFreq=zeros(size(histoAbsTimes));
                histoAbsAver=0;
                histoOccFreq=zeros(size(histoOccTimes));
                histoOccAver=0;
            end
```

```
            end
        occCumul=occCumul+occBuilding;
        if (optionHisto>0),
            histoAbsFreq=histoAbsFreq+histoAbsFreqBuilding;
            histoAbsAver=histoAbsAver+histoAbsAverBuilding/nb;
            histoOccFreq=histoOccFreq+histoOccFreqBuilding;
            histoOccAver=histoOccAver+histoOccAverBuilding/nb;
        end
    end % end of loop on buildings
    cpu2=toc;
end % of of option selection

% fprintf('CPU calculation of hourly occupancy probability profile: %6.2f
seconds\n',cpu1);
% fprintf('CPU drawing a random probability profile (altogether %i
persons):6.2f seconds\n',occMaxTot,cpu2);
% if (optionHisto>0),
%     fprintf('average block absence time: %6.2f hours\n',histoAbsAver);
%     if (optionHisto==1) fprintf('average daily occupancy time: %6.2f
hours\n',histoOccAver); end
%     if (optionHisto==2) fprintf('average weekly occupancy time: %6.2f
hours\n',histoOccAver); end
% end
%
% % display block absence time distribution
% if (optionHisto>0),
%     figure(1);
%     plot(histoAbsTimes/24,histoAbsFreq,'-rx');
%     grid on
%     title('Block absence time distribution (days)');
% end
%
% % display daily/weekly presence time distribution
% if (optionHisto>0)
%     figure(2);
%     plot(histoOccTimes,histoOccFreq,'-rx');
%     grid on
%     if (optionHisto==1) title('Daily presence time distribution (hours)');
end
%     if (optionHisto==2) title('Weekly presence time distribution (hours)');
end
% end
%
% % display time plot
% figure(3);
% td=t/86400;
% tdmin=td(1); tdmax=td(end);
% while (1),
%     tdlimit=input('Enter tdmin and tdmax [days] (return to stop): ','s');
%     if (strcmp(tdlimit,'')~=0), break; end
%     [tdmin,tdmax]=strread(tdlimit,'%f %f');
%     if (tdmin<td(1)), tdmin=td(1); end
%     if (tdmax>td(end)), tdmax=td(end); end
%     index=(td>=tdmin & td<=tdmax);
%     title1=input('Enter title: ','s');
%     plot(td(index),occCumul(index));
%     ylim([-0.2*occMaxTot,1.2*occMaxTot]);
```

```matlab
%     grid on
%     if (strcmp(title1,'')==0), title(title1); end
% end
```

```matlab
function SA = first_total_seq(k, Nrepl, N)

%Replicated estimations of first order, total order effects and total effects
by pairs of inputs
%using A, B and Ab.
%First order and total order indices are estimated according to the rule
proposed in
%Saltelli, A., P. Annoni, I. Azzini, F. Campolongo, M. Ratto, S. Tarantola,
(2010) Variance based sensitivity analysis of model output. Design and
estimator for the total sensitivity index, Computer Physics Communications,
181, 259-270
%Total cost = N(k+2)

% k = n of inputs
% Nrepl = n. of replicates
% N = number of base samples
% S = matrix (repl,k) of first order indices
% ST = matrix (repl,k) of total indices
% STij = matrix (repl,i,j) of pairs of total indices
% rmse = root mean square absolute error of total effects for ST

%Author: Stefano Tarantola
%Joint Research Centre of the European Commission
%Last release 27 September, 2010

for r = 1:Nrepl
    %vector of model output used to calculate output variance
      y4var=[];

      %generation of uniform samples in (0;1)
    for i=1:N
        X=[];
        T = LPTAU51(i+(r-1)*N,2*k);

        %PREPARATION OF THE RADIAL SAMPLE MATRIX X(k+2,k)
        A=T(1:k);
        B=T(k+1:2*k);
        X=[A;B];
        for j=1:k;
         Ab=A;
         Ab(j)=B(j);
         X=[X;Ab];
        end
         % model evaluation Y(k+2,1)

        %here write the function that calls your model
        %Example: y=rosenbrock(X);
        y=[];
        for j=1:k+2;
            y(j)=LtgNrgSA(X(j,1:k));
        end

        yA=y(1);
        yB=y(2);
        yAb=y(3:k+2);
```

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```matlab
        %vector for calculation of total variance
        y4var=[y4var;yA;yB];
        %compute nominators for first and totals
        for j=1:k
            Vi(i,j)=yB*(yAb(j)-yA);
            VT(i,j)=(yA-yAb(j))^2;
        end
        %calculation of total variance
        Vtot=var(y4var);
        %calculation of sensitivity indices
        %sequentially. Index i represents the sequentiality
        for j=1:k
          S(i,j)=mean(Vi(:,j))/Vtot;
          ST(i,j)=mean(VT(:,j))/2/Vtot;
        end
    end %N

      %compute nominators for totals of pairs of factors (they come at no
      %extra cost)
      %VTij(k+2,k,k) is a set of triangular matrices
    for i=1:N;
        for j=1:k
            yAbi=yAb(j);
            for j2=j+1:k
              yAbj=yAb(j2);
              VTij(i,j,j2)=(yAbi-yAbj)'*(yAbi-yAbj);
            end
        end
    end %N
    %calculation of total indices for pairs of factors (they come at no extra
cost)
    for j=1:k
        for j2=j+1:k
            STij(r,j2,j)=mean(VTij(:,j,j2))/2/Vtot;
        end
    end

end %r

save('y4var.mat');
save('Vi.mat');
save('VT.mat');
```

```matlab
function VECTOR = LPTAU(I, N)
```
%
%   I.M. SOBOL', V.I. TURCHANINOV, Yu.L. LEVITAN, B.V. SHUKHMAN
%   KELDYSH INSTITUTE OF APPLIED MATHEMATICS
%   RUSSIAN ACADEMY OF SCIENCES
%
%   QUASIRANDOM SEQUENCE GENERATORS
%   -------------------------------
%
%   28.11.1991
%
%   NOTE TO THE USER BY the NEA Data Bank:
%   This quasi random number generator has been made available to
%   you on condition that its identity is preserved when used
%   in computer programs. If its use leads to scientific publication
%   of results you should cite it in the references, in addition
%   no commercial use should be made unless agreed upon with the
%   main author (Prof. I.M. Sobol')
%
%   ABSTRACT
%   ....
%
%   POINTS BELONGING TO LP-TAU SEQUENCES UNIFORMLY DISTRIBUTED IN THE
%   N-DIMENSIONAL UNIT CUBE ARE OFTEN USED IN NUMERICAL MATHEMATICS:
%
%   - AS NODES FOR MULTIDIMENSIONAL INTEGRATION;
%   - AS SEARCHING POINTS IN GLOBAL OPTIMIZATION;
%   - AS TRIAL POINTS IN MULTI-CRITERIA DECISION MAKING;
%   - AS QUASIRANDOM POINTS FOR QUASI-MONTECARLO ALGORITHMS;
%   - ETC.
%
%   THIS SUBROUTINE CONTAINS THE ALGORITHM FOR FAST GENERATION OF
%   LP-TAU SEQUENCES THAT ARE SUITABLE FOR MULTI-PROCESSOR COMPUTATIONS.
%   THE DIMENSIONS N.LE.51, THE NUMBER OF POINTS N.LT.2**30.
%   THE PROGRAMMING LANGUAGE IS FORTRAN-77. THIS SUBROUTINE IS AVAILABLE
%   ALSO IN %-LANGUAGE.
%   THE REPORT DESCRIBING THE ALGORITHM CONTAINS THE DESCRIPTION OF THE
%   ALGORITHM AND CERTAIN IMPORTANT PROPERTIES OF LP-TAU SEQUENCES AND
%   THEIR GENERALIZATIONS ARE DISCUSSED.
%
%   REFERENCE:
%   I.M. SOBOL', V.I. TURCHANINOV, Yu.L. LEVITAN, B.V. SHUKHMAN
%   KELDYSH INSTITUTE OF APPLIED MATHEMATICS
%   RUSSIAN ACADEMY OF SCIENCES
%
%   QUASIRANDOM SEQUENCE GENERATORS
%   MOSCOW 1992, IPM ZAK. NO.30 (100 COPIES)
%
%   --
%
%   INPUT PARAMETERS:
%
%   I   -   NUMBER OF THE POINT (I=(0,2**30-1)),
%   N   -   DIMENSION OF THE POINT (0<N<52);
%
%   OUTPUT PARAMETER:

```matlab
%
%      VECTOR(N) - N-VECTOR CONTAINING THE CARTESIAN CO-ORDINATES OF
%                  THE I-TH POINT.
%
%
%      TO CALL THE SUBROUTINE WRITE:
%
%      CALL LPTAU(I,N,VECTOR)
%      WHERE I, N: INTEGER CAPABLE OF STORING 2**30 (INTEGER*4 ON IBM
%                  OR OTHER 32 BIT/WORD MACHINES)
%          VECTOR: DOUBLE PRECISION ARRAY WHOSE LENGTH < 52.
%
%       INTEGER QP
%      QP = QUANTITY POWER
%
%      PARAMETER (MAXDIM=51, QP=30, MAXNUM=2**30-1)
MAXDIM=51; QP=30; MAXNUM=2^30-1;
%
%      THE DIMENSION OF THE POINT CANNOT EXCEED MAXDIM
%      THE TOTAL NUMBER OF GENERATED POINTS CANNOT EXCEED 2**QP
%      MAXNUM=2**30-1 // 1073741823
%
%       DOUBLE PRECISION VECTOR(N)
%       INTEGER          I,N
%
%       INTEGER PRVNUM,PRVDIM
%       INTEGER DIRECT(MAXDIM,QP), MASKV(MAXDIM)
%       DOUBLE PRECISION SCALE
VECTOR=zeros(1,N);
SCALE =9.31322574615478516E-10;

persistent PRVNUM PRVDIM MASKV DIRECT
if isempty(PRVNUM), PRVNUM=-2; end,
if isempty(PRVDIM), PRVDIM=0; end,

if isempty(DIRECT), ...
        DIRECT(1:MAXDIM,1)=[
        536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912, 536870912, 536870912, 536870912, 536870912, ...
            536870912]';
    DIRECT(1:MAXDIM,2)=[
        805306368, 268435456, 805306368, 268435456, 805306368, ...
            268435456, 805306368, 268435456, 268435456, 805306368, ...
            268435456, 805306368, 268435456, 805306368, 268435456, ...
            805306368, 805306368, 268435456, 805306368, 268435456, ...
            805306368, 268435456, 805306368, 268435456, 268435456, ...
            805306368, 268435456, 805306368, 268435456, 805306368, ...
            268435456, 805306368, 805306368, 268435456, 805306368, ...
```

```
        268435456,    805306368,    268435456,    805306368,    268435456, ...
        268435456,    805306368,    268435456,    805306368,    268435456, ...
        805306368,    268435456,    805306368,    805306368,    268435456, ...
        805306368]';
DIRECT(1:MAXDIM,3)=[
    939524096,    939524096,    134217728,    671088640,    402653184, ...
        402653184,    671088640,    134217728,    671088640,    402653184, ...
        939524096,    134217728,    671088640,    939524096,    134217728, ...
        671088640,    134217728,    939524096,    939524096,    402653184, ...
        402653184,    134217728,    671088640,    402653184,    671088640, ...
        402653184,    402653184,    671088640,    134217728,    134217728, ...
        939524096,    939524096,    939524096,    939524096,    134217728, ...
        671088640,    402653184,    402653184,    671088640,    134217728, ...
        671088640,    402653184,    939524096,    134217728,    671088640, ...
        939524096,    134217728,    671088640,    134217728,    939524096, ...
        939524096]';
DIRECT(1:MAXDIM,4)=[
    1006632960,     67108864,    603979776,   1006632960,    335544320, ...
        469762048,    872415232,    738197504,    469762048,    872415232, ...
        1006632960,     67108864,    872415232,    469762048,    469762048, ...
        469762048,   1006632960,    335544320,    872415232,    603979776, ...
        201326592,     67108864,    335544320,     67108864,    201326592, ...
        738197504,   1006632960,    738197504,    603979776,    335544320, ...
        738197504,     67108864,   1006632960,     67108864,    603979776, ...
        1006632960,    335544320,    469762048,    872415232,    738197504, ...
        469762048,    872415232,   1006632960,     67108864,    872415232, ...
        469762048,    469762048,    469762048,   1006632960,    335544320, ...
        872415232]';
DIRECT(1:MAXDIM,5)=[
    1040187392,    637534208,   1040187392,    838860800,    167772160, ...
        234881024,    167772160,   1040187392,    436207616,     33554432, ...
        570425344,   1040187392,    503316480,    838860800,    973078528, ...
        167772160,    234881024,    436207616,    771751936,    100663296, ...
        234881024,    905969664,    771751936,     33554432,    838860800, ...
        973078528,    905969664,     33554432,    301989888,    838860800, ...
        100663296,    234881024,   1040187392,    637534208,   1040187392, ...
        838860800,    167772160,    234881024,    167772160,   1040187392, ...
        436207616,     33554432,    570425344,   1040187392,    503316480, ...
        838860800,    973078528,    167772160,    234881024,    436207616, ...
        771751936]';
DIRECT(1:MAXDIM,6)=[
    1056964608,    352321536,     50331648,    419430400,    956301312, ...
        889192448,    620756992,    117440512,    956301312,    922746880, ...
        822083584,    218103808,    587202560,    385875968,    452984832, ...
        218103808,    184549376,    285212672,    150994944,    956301312, ...
        352321536,    654311424,    553648128,    352321536,    788529152, ...
        956301312,    587202560,    251658240,    218103808,    721420288, ...
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DIRECT(1:MAXDIM,7)=[
    1065353216,   1065353216,    578813952,     25165824,    125829120, ...
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        159383552,    444596224,    947912704,    662700032,    444596224, ...
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DIRECT(1:MAXDIM,8)=[
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DIRECT(1:MAXDIM,9)=[
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     1059061760,  761266176,  673185792,  220200960,  396361728, ...
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      752877568,  387973120,  643825664,  291504128,  274726912, ...
      568328192,  526385152,  673185792,   98566144,  396361728, ...
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DIRECT(1:MAXDIM,10)=[
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      804257792,  495976448,  347078656,  426770432, 1066401792, ...
      372244480,   84934656,  208666624,  313524224,  598736896, ...
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      686817280,  592445440,  995098624,  498073600,  969932800, ...
      586153984, 1039138816,  814743552,  523239424,  294649856, ...
      305135616,  506462208,   11534336,  449839104,  619708416, ...
      479199232]';
DIRECT(1:MAXDIM,11)=[
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       25690112,  201850880,  443023360,  990380032,   63438848, ...
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      487063552,  363331584,  973602816,  286785536,  171442176, ...
      669515776,  110624768,  383254528,  289931264,  352845824, ...
      878182400,  655884288,  836239360,  765984768,  549978112, ...
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DIRECT(1:MAXDIM,12)=[
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     799801344,  261357568,  873201664,   40108032,  769392640, ...
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DIRECT(1:MAXDIM,13)=[
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     835059712,  949878784,  662044672,  767950848,  426901504, ...
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DIRECT(1:MAXDIM,14)=[
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     630652928,  340983808,  493944832,   37945344,  264175616, ...
     263520256,  833421312,  235077632,  464846848,  534839296, ...
     992411648,   10813440,  367067136,  116457472,  115015680, ...
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     267321344,  795803648,  635764736,  574160896, 1003421696, ...
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DIRECT(1:MAXDIM,15)=[
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     596541440,   42631168,  471433216,   52527104,  666861568, ...
     706707456,  674070528,  824410112,  305496064,  136282112, ...
     847740928,  531464192,  222920704,  379289600,  507740160, ...
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     133070848,  517046272,  129990656,  790396928,  563773440, ...
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DIRECT(1:MAXDIM,16)=[
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     407060480,  375275520,  256688128, 1021165568,  303349760, ...
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     789889024,  879575040,  764657664,  762658816, 1010843648, ...
     941080576,  827932672,   98942976, 1051738112,  624934912, ...
     993280000,  134070272,  201375744,  567558144,  882163712, ...
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     199278592,  815677440,  927678464,   94519296,  419184640, ...
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        747118592, 429973504, 1032609792, 932667392, 583360512, ...
        969498624, 1056333824, 660955136, 247488512, 153509888, ...
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DIRECT(1:MAXDIM,18)=[
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DIRECT(1:MAXDIM,19)=[
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DIRECT(1:MAXDIM,20)=[
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        907322368, 595696640, 247497728, 553735168, 826051584, ...
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        660327424, 284244992, 859868160, 722502656, 622844928, ...
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DIRECT(1:MAXDIM,21)=[
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        103878144, 325187072, 858254848, 922041856, 261924352, ...
        954978816, 292822528, 849512960, 210311680, 933232128, ...
        691981824, 155417088, 627070464, 416795136, 182081024, ...
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DIRECT(1:MAXDIM,22)=[
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DIRECT(1:MAXDIM,23)=[
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DIRECT(1:MAXDIM,24)=[
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DIRECT(1:MAXDIM,25)=[
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DIRECT(1:MAXDIM,26)=[
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      324351309,  609305915,  818137857,  131059769,  918519549, ...
      827341719,  922770101,  456972047,  363883221, 1057014661, ...
      900956063,  580478293,  520383687,  315470533,  227601711, ...
      169598765,  909227271,  796983815,  349496709,  393974911, ...
      378320037,  777004343,  927999269,  616377385,  345930959, ...
      989849787,  627400495,  892675125,  260314121, 1041964063, ...
      531367163,  195776757,  237309785,  949187605,  719002587, ...
      495745187]';
end
```

```matlab
%
%      TRAP FOR A WRONG SUBROUTINE CALL
%
if ((I<0) | (N<1) | (I>MAXNUM) | (N>MAXDIM)),
    disp('LP-TAU CALL FAILED')
    disp(' PRESS <ENTER> TO EXIT LPTAU')
    pause
    return
end
if ((PRVNUM+1==I) & (N<=PRVDIM)),
    %
    %       RECURRENT GENERATION OF THE POINT
    %
    %
    %       SEARCH POSITION OF THE RIGHTMOST  "1"
    %       IN THE BINARY REPRESENTATION OF I
    %
    L=0;
    POS=0;
    while L<QP & POS==0,
        L=L+1;
        POS=bitand(bitshift(I,-(L-1)),1);
    end
    %
    %       RIGHTMOST POSITION IS L
    %
    for J=1:N
        MASKV(J)=bitxor(MASKV(J),DIRECT(J,L));
        VECTOR(J)=MASKV(J)*SCALE;
    end
else
    %
    %       GENERATION OF THE POINT FROM "I" AND "N"
    %
    MASKV=zeros(1,N);
    IM=bitxor(I,bitshift(I,-1));
    M=0;
    while IM~=0 & M<QP,
        M=M+1;
        if (bitand(IM,1)==1),
            for J=1:N
                MASKV(J)=bitxor(MASKV(J),DIRECT(J,M));
            end
        end
        IM=bitshift(IM,-1);
    end
    for J=1:N
        VECTOR(J)=MASKV(J)*SCALE;
    end
end
%
PRVNUM=I;
PRVDIM=N;
return
```

APPENDIX B: MATLAB CODE FOR OCCUPANCY MODEL ADJUSTMENT AND

VALIDATION

```matlab
function [occCumul,histoAbsTimes,histoAbsFreq,histoAbsAver,...
    histoOccTimes,histoOccFreq,histoOccAver]=...
    occmodelmod(t,occInit,occMax,shuff,probHour,...
    nAbsAver,absDurationProb,absDurationBin,absDurationMin,...

firstDay,histoFlag,histoAbsBin,histoAbsNBin,histoOccBin,histoOccNBin,alpha,la
mbda,delta,nu)
% calculation of cumulated effective occupancy
% for occMax persons, for the times given in the nt array
% version 1.4: add absence blocks

% Parameters:
% - t              = array of times for which occupancy will be calculated
[s]
% - occInit        = initial value of occupancy (0 or 1)
% - occMax         = number of persons
% - shuff          = shuffling parameter
% - probHour       = array of hourly occupancy probability profiles
% - nAbsAver       = average number of absences during one year
% - absDurationProb = array of absence duration probability
% - absDurationBin = absence duration probability bin [hours]
% - absDurationMin = absence duration minimum [hours]
% - firstDay       = first day of the year (1=Monday, 2=Tuesday, ...
7=Sunday)
% - histoFlag      = occupancy histogram (0=no histogram, 1=per day, 2=per
week)
% - histoAbsBin    = absence duration histogram bin [hours]
% - histoAbsNBin   = absence duration histogram number of bins
% - histoOccBin    = occupancy histogram bin [hours]
% - histoOccNBin   = occupancy histogram number of bins
% Outputs:
% - occCumul       = cumulated occupancy corresponding to the t array
% - histoAbsTimes  = times for the block absence histogram [hours]
% - histoAbsFreq   = values (frequencies) for the block absence histogram
% - histoAbsAver   = average block absence time [hours]
% - histoOccTimes  = times for the daily occupancy histogram [hours]
% - histoOccFreq   = values (frequencies) for the daily/weekly occupancy
histogram
% - histoOccAver   = average of daily/weekly occupancy time
%
% The first output argument is mandatory; all the others are optional,
% but they should be either all present or all absent; they should
% be present if histoFlag>0
%
% For each person, an independent occupancy
% profile is drawn at random, using the
% transition probability time arrays T01 and T11

% indexes:
% index1(k=1 to nprobHour)=pointer to plist element corresponding to
```

```matlab
% the hourly profile element k (value: 1 to nplist)
% index2(i=1 to nt)=pointer to plist element corresponding to the
% time step i (value: 1 to nplist)

% check number of input and output arguments
% if (nargin~=10 & nargin~=15)
%     error('*** occrandom1 error: nargin = %i, should be 10 or 15',nargin)
% end
% if (nargout~=1 & nargout~=7)
%     error('*** occrandom1 error: nargin = %i, should be 1 or 7',nargout)
% end
% if (histoFlag>0 & nargout~=7)
%     error('*** occrandom1 error: nargin = %i, should be 7 because
histoFlag>0',nargout)
% end
%% RT1
% calculate the possible occupancy probabilities
% it is supposed that the maximum number of different
% occupancy probability values is PMAX = 10
% (if larger, the function stops with an error message)
% % % % % nprobHour=length(probHour);
% % % % % index1=zeros(1,nprobHour);
% % % % % NPMAX=4*24*7;
% % % % % plist=zeros(1,NPMAX);
% % % % % nplist=1; plist(1)=0; index1(1)=1; % first element = zero occupancy
probability
% % % % % for k=1:nprobHour,
% % % % %     pfound=find(probHour(k)==plist(1:nplist));
% % % % %     if (length(pfound)==0),
% % % % %         % found new probability value
% % % % %         if (nplist<NPMAX),
% % % % %             nplist=nplist+1; plist(nplist)=probHour(k);
index1(k)=nplist;
% % % % %         else
% % % % %             error('*** occrandom1 error: more than %i probability
values',NPMAX)
% % % % %         end
% % % % %     else
% % % % %         % already existing probability value
% % % % %         index1(k)=pfound(1);
% % % % %     end
% % % % % end
% % % % %
% % % % % % calculate transition probability matrices T01 and T11
% % % % % T01list=zeros(NPMAX,NPMAX);
% % % % % T11list=zeros(NPMAX,NPMAX);
% % % % % for j1=1:NPMAX,
% % % % %     for j2=1:NPMAX,
% % % % %
[T01list(j1,j2),T11list(j1,j2)]=occtrans1(plist(j1),plist(j2),shuff);
% % % % %     end
% % % % % end
%% RT2 ===========================BEGIN MAIN CODE=========================
%ADD FOUR PARAMETER MODIFICATION TO probHour
probHour1=weektrans(probHour,alpha,lambda,delta,nu);  %Function to employ
alpha, lambda, delta and nu
```

```matlab
T01List=zeros(1,length(probHour1));
T11List=zeros(1,length(probHour1));
for j=1:length(probHour)-1
    [T01List(j),T11List(j)]=occtrans1(probHour1(j),probHour1(j+1),shuff);
end

% calculate occupancy probability time arrays
nt=length(t);
dt=t(2)-t(1);
daynb=zeros(1,nt);
weeknb=zeros(1,nt);
index2=zeros(1,nt); % for each timestep, index in the plist array
pBlockAbs=nAbsAver/nt; % probability of starting a block absence at each
timestep

for i=1:nt,
    tday=mod(t(i),86400); % time in the day
    daynb(i)=fix(t(i)/86400); % day number in the year
    weeknb(i)=fix((daynb(i)+firstDay+5)/7); % week number in the year (1 to
53)
    h=fix(tday/3600); % full hour in the day
    m=month1(daynb(i)); % month number (1 to 12)
    weekday=mod(daynb(i)+firstDay-2,7)+1; % day of the week (1 to 7)
    if (weekday==6) w=2; % Saturday
    elseif (weekday==7) w=3; % Sunday
    else w=1; end % weekday
    k=h+1+24*(w-1)+3*24*(m-1); % index in the probHour array
%    index2(i)=index1(k); % index in the plist array
end

% time distribution of block absence: calculate cumulative distribution
% function and prepare histogram
nabs=length(absDurationProb);
absDurationProbCumul=cumsum(absDurationProb); % cumulative probability
if (abs(absDurationProbCumul(nabs)-1)>nabs*eps)
    error('*** occrandom1 error: absDurationProbCumul(%i) = %f, should be
1',nabs,absDurationProbCumul(nabs))
end
% preparing bins for the distribution of periods of long absence
if (histoFlag>0)
    hmax=histoAbsBin*(histoAbsNBin-1); % value for the beginning of last bin
    histoAbsTimes=[0:histoAbsBin:hmax];
    histoAbsFreq=zeros(1,histoAbsNBin);
    histoAbsAver=0;
    histoAbsTot=0;
end

% time distribution of daily/weekly occupancy: prepare histogram
if (histoFlag>0)
    hmax=histoOccBin*(histoOccNBin-1); % value for the beginning of last bin
    histoOccTimes=[0:histoOccBin:hmax];
    histoOccFreq=zeros(1,histoOccNBin);
    histoOccAver=0;
    histoOccTot=0;
end
```

```matlab
% calculate occupancy simulated by the stochastic model
occCumul=zeros(1,nt);
for k=1:occMax
    occ0=occInit; % initial value of occupancy
    blockAbs0=0; % initial value of block absence: 0 (normal occupancy)
    occCumul(1)=occCumul(1)+occ0;
    occtime=0; % initial value of daily/weekly occupation time [hours]
    if (histoFlag==1) daynb0=daynb(1); end
    if (histoFlag==2) weeknb0=weeknb(1); end
    for i=1:nt-1
        % if nargout>1 and day/week has changed, increment the daily/weekly
occupation histogram
        if (histoFlag==1 & daynb(i)>daynb0)
            j=fix(occtime/histoOccBin)+1;
            if (j>=1 & j<=histoOccNBin)
                histoOccFreq(j)=histoOccFreq(j)+1;
            end
            histoOccAver=histoOccAver+occtime; histoOccTot=histoOccTot+1;
            daynb0=daynb(i);
            occtime=0;
        elseif (histoFlag==2 & weeknb(i)>weeknb0)
            j=fix(occtime/histoOccBin)+1;
            if (j>=1 & j<=histoOccNBin)
                histoOccFreq(j)=histoOccFreq(j)+1;
            end
            histoOccAver=histoOccAver+occtime; histoOccTot=histoOccTot+1;
            weeknb0=weeknb(i);
            occtime=0;
        end
        % determine whether a block absence should start
        if (blockAbs0==0) % currently not in a block absence
            x=rand(1);
            if (x<pBlockAbs)
                blockAbs=1; % start a block absence
                % determine the duration of block absence
                x=rand(1);
                g=find(absDurationProbCumul<x);
                x=rand(1);
                dBlockAbs=(length(g)+x)*absDurationBin+absDurationMin;
%hours, minimum absDurationMin
                tEndBlockAbs=t(i)+dBlockAbs*3600;
                if (histoFlag>0)
                    j=fix(dBlockAbs/absDurationBin)+1;
                    if (j>=1 & j<=histoAbsNBin)
                        histoAbsFreq(j)=histoAbsFreq(j)+1;
                    end
                    histoAbsAver=histoAbsAver+dBlockAbs;
                end
            else
                blockAbs=0;
            end
        else % currently in a block absence, check possible end
            if (t(i)>tEndBlockAbs)
                blockAbs=0;
            else
                blockAbs=1;
```

```matlab
                end
            end
% % % % %          if (blockAbs0==0), j1=index2(i);
% % % % %          else j1=1; end
% % % % %          if (blockAbs==0), j2=index2(i+1);
% % % % %          else j2=1; end
% % % % %          T01=T01list(j1,j2);
% % % % %          T11=T11list(j1,j2);
        if (blockAbs==1) % occupant just left on long absence
            occ=0;
        elseif (blockAbs0==1)&&(blockAbs==0) % occupant just came back from
long absence
            occ=1;
        else
            T01=T01List(mod(i-1,672)+1);
            T11=T11List(mod(i-1,672)+1);
            x=rand(1);
            if (occ0==0) % room currently not occupied
                if (T01>x)
                    occ=1;
                else
                    occ=0;
                end
            elseif (occ0==1) % room currently occupied
                T10=1-T11;
                if (T10>x)
                    occ=0;
                else
                    occ=1;
                end
            end
        end
        occ0=occ;
        blockAbs0=blockAbs;
        occCumul(i+1)=occCumul(i+1)+occ;
        if (histoFlag>0)
            occtime=occtime+dt*occ/3600;
        end
    end % loop through time period  *RT
end % loop for each occupant  *RT

% average values
if (histoFlag>0),
    if (histoAbsTot>0),
        histoAbsAver=histoAbsAver/histoAbsTot;
    end
    if (histoOccTot>0),
        histoOccAver=histoOccAver/histoOccTot;
    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
```

```matlab
function m=month1(daynb)
% calculate month number (1 to 12) corresponding to daynb
% (number of day in the year, from 1 to 365)
% current version: no leap year !

firstday=[1,32,60,91,121,152,182,213,244,274,305,335,9999];
m1=find(daynb<firstday);
m=m1(1)-1;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%


function [T01,T11]=occtrans1(pcurr,pnext,shuff)
% calculation of transition probability, model 1
% T01=probability of transition 0 -> 1
% T11=probability of transition 1 -> 1
% (note: T00=1-T01, T10=1-T11)
% pcurr=current step occupancy probability
% pnext=next step occupancy probability
% shuff = shuffling parameter
% beta = adjusted value of shuff

beta=shuff; % default: no adjustment needed

if(pnext==0)
    T01=0;
    T11=0;
elseif(pnext==1)
    T01=1;
    T11=1;
else
    if (pcurr==1)
        T11=pnext;
        T01=0;
    elseif (pcurr==0)
        T01=pnext;
        T11=0;
    elseif (pcurr==pnext)
        if (pcurr+pnext>1)
            if (shuff>1/(2*pcurr-1))
                beta=1/(2*pcurr-1);
            else
                beta=shuff;
            end
        elseif (pcurr+pnext<1)
            if (shuff>1/(1-2*pcurr))
                beta=1/(1-2*pcurr);
            else
                beta=shuff;
            end
        else
            beta=shuff;
        end
```

```matlab
        T01=2*beta*pcurr/(beta+1);
        T11=1-(1-pcurr)*T01/pcurr;
    elseif (pcurr<pnext)
        if (shuff<(pnext-pcurr)/(2-(pnext+pcurr)))
            beta=(pnext-pcurr)/(2-(pnext+pcurr));
        else
            if ((pcurr+pnext>1) & (shuff>(pcurr-pnext+1)/(pnext+pcurr-1)))
                beta=(pcurr-pnext+1)/(pnext+pcurr-1);
            elseif ((pcurr+pnext<1) & (shuff>(1-pcurr+pnext)/(1-pcurr-
pnext)))
                beta=(1-pcurr+pnext)/(1-pcurr-pnext);
            else
                beta=shuff;
            end
        end
        T01=pnext+pcurr*(beta-1)/(beta+1);
        T11=1/pcurr*(pnext-(1-pcurr)*T01);
    else % (pcurr>pnext)
        if (shuff<(pcurr-pnext)/(pnext+pcurr))
            beta=(pcurr-pnext)/(pnext+pcurr);
        else
            if ((pcurr+pnext>1) & (shuff>(pcurr-pnext+1)/(pnext+pcurr-1)))
                beta=(pcurr-pnext+1)/(pnext+pcurr-1);
            elseif ((pcurr+pnext<1) & (shuff>(1-pcurr+pnext)/(1-pcurr-
pnext)))
                beta=(1-pcurr+pnext)/(1-pcurr-pnext);
            else
                beta=shuff;
            end
        end
        T01=pnext+pcurr*(beta-1)/(beta+1);
        T11=1/pcurr*(pnext-(1-pcurr)*T01);
    end
end

% print a message if shuff and beta are not equal
% if (beta~=shuff)
%     fprintf('***Warning: the shuffling parameters had to be adjusted\n');
%     fprintf('           pcurr=%6.2f, pnext=%6.2f, shuff=%6.2f adjusted to
%6.2f\n',...
%         pcurr,pnext,shuff,beta)
% end
```

```matlab
function[occCumul,histoOccTimes,histoOccFreq,histoOccAver,histoAbsTimes,...
    histoAbsFreq,histoAbsAver]=
occtestmod(NumberOfBuildings,NumberOfPeople,...
                            AverageNumberofLongAbsences,...
                            LongAbsenceProbabilityDistribution,...
                            MuParameter,...
                            ProbabilityProfile,alpha,lambda,delta,nu)
% histoAbsAver,
% histoOccAver,
% histoAbsTimes/24,histoAbsFreq,
% histoOccTimes,histoOccFreq,

% script occupancy model 1.4 (now it's a function so I can enter my
parameters easily)
% generation of an occupancy profile
% occMax=maximum number of persons in the zone
% tmin=minimum generation time [s]
% tmax=maximum generation time [s]
% dt=calculation timestep [s]
% [t1,t2]=morning occupancy interval [s]
% [t3,t4]=afternoon occupancy interval [s]
% p1=occupancy probability for t<t1 or t>t4, or week-end
% p2=occupancy probability for [t1,t2]
% p3=occupancy probability for [t2,t3]
% p4=occupancy probability for [t3,t4]
% shuff=shuffling parameter

nb=NumberOfBuildings; % number of buildings
occMaxBuilding=NumberOfPeople; % max occupancy for each building
occMaxTot=occMaxBuilding*nb;
tmin=1*86400;
tmax=(1*365+1)*86400;
dt=900;
shuff=MuParameter;
nAbsAver=AverageNumberofLongAbsences; % average number of block absences
during the considered period
absDurationProb=LongAbsenceProbabilityDistribution; % block absence
probabilities
absDurationBin=12; % bin for the block absence probability [hours]
absDurationMin=12; % minimum block absence duration [hours]
histoAbsBin=6; % absence histogram bin [hours]
histoAbsNBin=100; % absence histogram number of bins
histoOccBin= 1/4; % daily/weekly occupancy histogram bin [quarters of an
hour]
histoOccNBin=100*4; % daily/weekly occupancy histogram number of bins

% generation of time array and initialization
t=[tmin:dt:tmax]; nt=length(t); % nt = number of time steps
occ0=0; % initial value: room supposed to be unoccupied
occCumul=zeros(size(t));
firstDay=1; % arbitrary value (Monday)

% options
optionBuilding=1; % 1=all buildings together, 2=each building separately
optionHisto=2; % 0=no histogram, 1=daily occupancy histogram, 2=weekly
occupancy histogram
```

```matlab
% calculate occupancy probability array, hour by hour:
% for each month, 3 daily profiles (24 values) for
% Mondays to Fridays, Saturdays, Sundays
% --> altogether 12 * 3 * 24 = 864 values
tic;
%probhour=probhour_Office003(WeekdayHourlyProbProfile,SaturdayHourlyProbProfi
le,SundayHourlyProbProfile);
probhour=ProbabilityProfile;
cpu1=toc;
if (optionBuilding==1),
    % calculate occupancy simulated by stochastic model
    % optionBuilding==1: all buildings calculated at once, only one function
call
    tic;
    if (optionHisto==0),
        occCumul=...
            occmodelmod(t,occ0,occMaxTot,shuff,probhour,nAbsAver,...

absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto,alpha,lamb
da,delta,nu);
    elseif (optionHisto>0),
        [occCumul,histoAbsTimes,histoAbsFreq,histoAbsAver,...
            histoOccTimes,histoOccFreq,histoOccAver]=...
            occmodelmod(t,occ0,occMaxTot,shuff,probhour,nAbsAver,...

absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto,...

histoAbsBin,histoAbsNBin,histoOccBin,histoOccNBin,alpha,lambda,delta,nu);
    end
    cpu2=toc;
elseif (optionBuilding==2),
    % calculated occupancy simulated by stochastic model
    % optionBuilding==2: every building calculated with a different profile,
nb function calls
    tic;
    for i=1:nb % loop on buildings
        if (optionHisto==0),
            occBuilding=...
                occmodel(t,occ0,occMaxBuilding,shuff,probhour,nAbsAver,...

absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto);
        elseif (optionHisto>0),

[occBuilding,histoAbsTimes,histoAbsFreqBuilding,histoAbsAverBuilding,....
                histoOccTimes,histoOccFreqBuilding,histoOccAverBuilding]=...
                occmodel(t,occ0,occMaxBuilding,shuff,probhour,...

nAbsAver,absDurationProb,absDurationBin,absDurationMin,firstDay,optionHisto,.
..
                histoAbsBin,histoAbsNBin,histoOccBin,histoOccNBin);
        end
        if (i==1)
            occCumul=zeros(size(t));
            if (optionHisto>0),
                histoAbsFreq=zeros(size(histoAbsTimes));
                histoAbsAver=0;
```

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```matlab
                    histoOccFreq=zeros(size(histoOccTimes));
                    histoOccAver=0;
                end
            end
            occCumul=occCumul+occBuilding;
            if (optionHisto>0),
                histoAbsFreq=histoAbsFreq+histoAbsFreqBuilding;
                histoAbsAver=histoAbsAver+histoAbsAverBuilding/nb;
                histoOccFreq=histoOccFreq+histoOccFreqBuilding;
                histoOccAver=histoOccAver+histoOccAverBuilding/nb;
            end
        end
    end % end of loop on buildings
    cpu2=toc;
end % of of option selection

% fprintf('CPU calculation of hourly occupancy probability profile: %6.2f
seconds\n',cpu1);
% fprintf('CPU drawing a random probability profile (altogether %i
persons):6.2f seconds\n',occMaxTot,cpu2);
% if (optionHisto>0),
%     fprintf('average block absence time: %6.2f hours\n',histoAbsAver);
%     if (optionHisto==1) fprintf('average daily occupancy time: %6.2f
hours\n',histoOccAver); end
%     if (optionHisto==2) fprintf('average weekly occupancy time: %6.2f
hours\n',histoOccAver); end
% end
%
% % display block absence time distribution
% if (optionHisto>0),
%     figure(1);
%     plot(histoAbsTimes/24,histoAbsFreq,'-rx');
%     grid on
%     title('Block absence time distribution (days)');
% end
%
% % display daily/weekly presence time distribution
% if (optionHisto>0)
%     figure(2);
%     plot(histoOccTimes,histoOccFreq,'-rx');
%     grid on
%     if (optionHisto==1) title('Daily presence time distribution (hours)');
end
%     if (optionHisto==2) title('Weekly presence time distribution (hours)');
end
% end
%
% % display time plot
% figure(3);
% td=t/86400;
% tdmin=td(1); tdmax=td(end);
% while (1),
%     tdlimit=input('Enter tdmin and tdmax [days] (return to stop): ','s');
%     if (strcmp(tdlimit,'')~=0), break; end
%     [tdmin,tdmax]=strread(tdlimit,'%f %f');
%     if (tdmin<td(1)), tdmin=td(1); end
%     if (tdmax>td(end)), tdmax=td(end); end
%     index=(td>=tdmin & td<=tdmax);
```

```matlab
%       title1=input('Enter title: ','s');
%       plot(td(index),occCumul(index));
%       ylim([-0.2*occMaxTot,1.2*occMaxTot]);
%       grid on
%       if (strcmp(title1,'')==0), title(title1); end
% end
```

```matlab
function [probHour2]=occtrans0(probHour,alpha,lambda,delta,nu);
%   adjusts POP data based on four new parameters
%   alpha makes occupied day start earlier/later
%   lambda makes occupied day longer/shorter
%   delta increases/decreases occupancy during occupied hours
%   nu increases/decreases occupancy during unoccupied hours

%First alpha
DDL = 60;  %indexed default day length 15 hours
StartTime = alpha + 6;  %sets start of day time
StartIndex = StartTime*4;   %indexes start of day
EndIndex = StartTime*4+DDL;   %indexes end of day   WITHOUT LAMBDA ADJ
offset = alpha*4;   %Indexed numerical offset for alpha adjustment
if alpha == 0   %no change to start time
    for j = 1:length(probHour); %whole day
        probHour1(j)=probHour(j);   %no change
    end
elseif alpha < 0;   %day starts earlier
    for j = 1:StartIndex;  %before day begins
        probHour1(j) = probHour(j); %no change
    end
    for j = 24:96;   %finish daytime of current POPs shifting forward
        probHour1(j+offset) = probHour(j);  %shift remainder of day earlier
    end
    for j = (96+offset):96;   %finish daytimme hours
        probHour1(j) = probHour1(j-1);  %repeat last POP for rest of day
    end
else     %if alpha > 0, day starts later
    for j = 1:24;   %first 6 hours
        probHour1(j) = probHour(j); %no change
    end
    for j = 25:StartIndex;   %between 6a and start time
        probHour1(j) = probHour1(j-1);
    end
    for j = StartIndex + 1:96;   %finish day
        probHour1(j) = probHour(j-offset);
    end
end

%Then lambda IN DECIMAL HOURS
if lambda == 0; %no adjustment
    EndIndex1 = EndIndex;
    for j = 1:length(probHour); %full day
        probHour2(j)=probHour1(j)    %no adjustment
    end
else
    for j =1:StartIndex;     %Fill in beginning of day
        probHour2(j)=probHour1(j)   %POP unchanged before day starts
    end
    EndTime1 = StartTime + 15 + lambda;     %clock time for end of adjusted
day
    EndIndex1 = EndTime1 * 4;   %index to use for adjusted end of day
    ADL = EndIndex1 - StartIndex;   %lambda-adjusted day length index
    loffset = DDL - ADL;    %index offset for lambda adjustment
    for j = 1:ADL;   %Start after start of day
        PopTime=DDL/ADL*j;    %Matching value
```

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```matlab
        IndexMin = floor(PopTime);   %Bracket low index
        IndexMax = ceil(PopTime);    %Bracket high index
        if (IndexMax + StartIndex) >= 96;
            LowPOP = probHour1(96);
            HighPOP = probHour1(96);
        else
            LowPOP = probHour1(IndexMin + StartIndex);  %Lookup POP at low
index
            HighPOP = probHour1(IndexMax +  StartIndex);    %Lookup POP at
high index
        end
        if IndexMin == IndexMax;
            probHour2(j+StartIndex) = LowPOP;
        else
            probHour2(j+StartIndex) = (HighPOP - LowPOP)/(IndexMax-
IndexMin)*(PopTime-IndexMin)+LowPOP;    %Linear interp of POP
        end
    end
    if lambda < 0;  %if day gets shorter
        for j = 1:(96-EndIndex);  %Fill in from remaining POP after day ends
            probHour2(EndIndex1+j) = probHour1(EndIndex + j);
        end
        for j = (96-loffset):96;   %repeat last POP to close-out day
            probHour2(j) = probHour2(j-1);
        end
    elseif lambda > 0;     %if lambda > 0 and day gets longer
        for j = (EndIndex1 + 1):96;
            probHour2(j) = probHour1(j+loffset);
        end
    end
end


%Then delta
if EndIndex1 > 96;
    for j = StartIndex:96;
        probHour2(j) = min(probHour2(j)*delta,1);
    end
else
    for j = StartIndex:EndIndex1;
        probHour2(j) = min(probHour2(j)*delta,1);
    end
end


%Then nu
for j = 1:StartIndex;
    probHour2(j) = min(probHour2(j)*nu,1);
end
if EndIndex1 <= 96;
    for j = EndIndex1:96;
        probHour2(j) = min(probHour2(j)*nu,1);
    end
end
```

```
function [adjWeekPOP] = weektrans(probHour, alpha, lambda, delta, nu);
%takes given weekly POP data and parses to daily data
%then calls occtrans0, which applies alpha, lambda, delta and nu adj

for j = 1:7;     %each day of the week
   for k = 1:96;      %each data point for each day
       TempProbHour(k)=probHour((j-1)*96+k);
   end

   tempadj = occtrans0(TempProbHour,alpha,lambda,delta,nu);

   for k = 1:96;     %each data point for each day
       adjWeekPOP((j-1)*96+k)=tempadj(k);
   end
end
```

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```
%************************************************************************
%
%   FUNCTION
%   generateOccupancyWithAdj
%
%   DESCRIPTION
%   Generates a new occupancy profile for the year specified. replaces
%   occupancy information in the input structure with new occupancy.
%   Modified to include four additional parameters to adjust time-series.
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years yet. [and energyplus would barf if it got anything
%         with more or less than 8760 values anyway...]
%   nZones: the number of individuals or single-occupancy zones
%   mu: mobility parameter (Page original); may or may not be an input
%   alpha: arrival parameter, [hours around 6a typical start]
%   lambda: day  length parameter, [ratio of actual length over 15 hour
%   std]
%   delta: daytime occupancy adjustment, 1 for no adjustment
%   nu: nighttime occupancy adjustment, 1 for no adjustment
%
%   OUTPUT
%   occout: a structure containing the following:
%     .year
%     .month
%     .day
%     .hour
%     .minute
%     .val  = this is a fractional value of the total number of people
present;
%
%   ORIGINAL AUTHOR
%   Ryan Tanner
%   University of Colorado at Boulder
%   ryan.tanner@colorado.edu
%
%   ORIGINAL DATE
%   27.Mar.2011
%
%   MODIFICATION AUTHOR
%   Darcie Chinnis
%   University of Colorado
%   darcie.oconnor@colorado.edu
%
%   NOTES
%   May.2011 Currently the occupancy algorithm generates data at 15-min
%   intervals and generates enough for exactly one year plus one increment
%   (34041 fifteen-minute intervals)
%
%   14.Sep.2011 Added some commenting.
%
%   May.2012 Adding four additional parameters for profile modification
%
%************************************************************************
```

```matlab
function occout = generateOccupancy(year,nzones,mu,alpha,lambda,delta,nu)


load('SampleInputs.mat')
NumberOfBuildings=1;
NumberOfPeople=1;
% j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
time=(1:(8760*4))*15*60; % generate 15-minute intervals for a year [in
SECONDS]
time=[time,8760*4*15*60+15*60]; % add one more interval to match occupancy
output from the Page programs
    occout.year(35041)  = 0;
    occout.month(35041) = 0;
    occout.day(35041)   = 0;
    occout.hour(35041)  = 0;
    occout.minute(35041)= 0;
    occout.val(nzones,35041)   = 0;


for zone = 1:nzones
    j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
    %generate 15-minute occupancy data using the Page Algorithm
    Occupancy=occtestmod(NumberOfBuildings,NumberOfPeople,...
    LongAbsences{j}.averagenumberperyear,...
    LongAbsences{j}.probability,...
    mu,...
    ProbabilityProfiles{j}.probability,alpha,lambda,delta,nu);
    month=1;
    day=1;
    hour=0;
    % mins=0;
    % sec=0;
    count=1;
    for ii=2:length(Occupancy)

        % create output values for year, month, day, hour and minute if at
        % exact hourly value
        if mod(time(ii),3600)==0; % if we're at an hourly value[1:00, 4:00,
15:00, etc...], this is true!,
            hour=hour+1;
            minute = 0;

            if hour > 24 % if we're at hour 25, we move to the next day,
first hour
                hour=1;
                day=day+1;

                if day > eomday(year, month) %eomday is the ending day of the
month: 31 for jan, mar, 28/29 for feb, 30 for april, etc.
                                         %if we're at day 32 for january,
move to february
                    day=1;
                    month=month+1;
```

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```matlab
            end

        end

    %create output values for year, month, day, hour and minute if NOT
    %at exact hourly value
    else
        %calculate minutes
        if ii == hour*4 + 1;
            minute = 15;
        elseif ii == hour*4 + 2;
            minute = 30;
        else ii == hour*4 + 3;
            minute = 45;
        end

    end %ends 15-minute loop

    % at this point we've established what year, month, day, and
    % hour and minute we are at.

    %within the hourly loop, set values for the occupancy output
    %structure
    occout.year(count)      = year;
    occout.month(count)     = month;
    occout.day(count)       = day;
    occout.hour(count)      = hour;
    occout.minute(count)    = minute;
    occout.val(zone,count)  = Occupancy(ii);

    % [ARTIFACT OF RYAN's MODEL]
    % Now comes the tricky part; how to turn 15-minute data into
    % hourly data? As of this revision, we take the average of
    % occupancy over the last four 15-minute intervals, and round
    % that number up with the 'ceil' command. Then we divide by the
    % total number of people to get a fractional value of total
    % occupancy, (between zero and 1, naturally) which Energyplus
    % can interpret and multiply by an occupant density to get the
    % right number of people.
    % occout.val(zone,count)  = ceil(mean(Occupancy(ii-
3:ii)))/NumberOfPeople;

    if count==35041; %stop when we get to the end of the year
        break
    end

    count=count+1;

    end % of looping through 34041 occupancy entries
end % of zonal loop
OccProfile=occout.val;
end % of function
```

```
%************************************************************************
%
%   FUNCTION
%   generateOccupancyWithAdj
%
%   DESCRIPTION
%   Generates a new occupancy profile for the year specified. replaces
%   occupancy information in the input structure with new occupancy.
%   Modified to include four additional parameters to adjust time-series.
%
%   ARGUMENTS
%   year: the year that we are using; this program does not account for
%         leap-years yet. [and energyplus would barf if it got anything
%         with more or less than 8760 values anyway...]
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%   mu: mobility parameter (Page original); may or may not be an input
%   alpha: arrival parameter, [hours around 6a typical start]
%   lambda: day  length parameter, [ratio of actual length over 15 hour
%   std]
%   delta: daytime occupancy adjustment, 1 for no adjustment
%   nu: nighttime occupancy adjustment, 1 for no adjustment
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%   occout: a structure containing the following:
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%   (34041 fifteen-minute intervals)
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%
%   May.2012 Adding four additional parameters for profile modification
%
%************************************************************************
```

```matlab
function occout = generateOccupancy(year,nzones,alpha,lambda,delta,nu)

load('SampleInputs.mat')
NumberOfBuildings=1;
NumberOfPeople=1;
% j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
time=(1:(8760*4))*15*60; % generate 15-minute intervals for a year [in
SECONDS]
time=[time,8760*4*15*60+15*60]; % add one more interval to match occupancy
output from the Page programs
    occout.year(35041)  = 0;
    occout.month(35041) = 0;
    occout.day(35041)   = 0;
    occout.hour(35041)  = 0;
    occout.minute(35041)= 0;
    occout.val(nzones,35041)    = 0;

for zone = 1:nzones
    j=ceil(rand*20); % there are 20 options in the LongAbsences, MuProfiles,
and ProbabilityProfiles structures; j refers to the first element
    %generate 15-minute occupancy data using the Page Algorithm
    Occupancy=occtestmod(NumberOfBuildings,NumberOfPeople,...
    LongAbsences{j}.averagenumberperyear,...
    LongAbsences{j}.probability,...
    MuProfiles{j}.mean,...
    ProbabilityProfiles{j}.probability,alpha,lambda,delta,nu);
    month=1;
    day=1;
    hour=0;
    % mins=0;
    % sec=0;
    count=1;
    for ii=2:length(Occupancy)

        % create output values for year, month, day, hour and minute if at
        % exact hourly value
        if mod(time(ii),3600)==0; % if we're at an hourly value[1:00, 4:00,
15:00, etc...], this is true!,
            hour=hour+1;
            minute = 0;

            if hour > 24 % if we're at hour 25, we move to the next day,
first hour
                hour=1;
                day=day+1;

                if day > eomday(year, month) %eomday is the ending day of the
month: 31 for jan, mar, 28/29 for feb, 30 for april, etc.
                                            %if we're at day 32 for january,
move to february
                    day=1;
                    month=month+1;
```

```matlab
            end

        end

        %create output values for year, month, day, hour and minute if NOT
        %at exact hourly value
        else
            %calculate minutes
            if ii == hour*4 + 1;
                minute = 15;
            elseif ii == hour*4 + 2;
                minute = 30;
            else ii == hour*4 + 3;
                minute = 45;
            end

        end %ends 15-minute loop

        % at this point we've established what year, month, day, and
        % hour and minute we are at.

        %within the hourly loop, set values for the occupancy output
        %structure
        occout.year(count)      = year;
        occout.month(count)     = month;
        occout.day(count)       = day;
        occout.hour(count)      = hour;
        occout.minute(count)    = minute;
        occout.val(zone,count)  = Occupancy(ii);

        % [ARTIFACT OF RYAN's MODEL]
        % Now comes the tricky part; how to turn 15-minute data into
        % hourly data? As of this revision, we take the average of
        % occupancy over the last four 15-minute intervals, and round
        % that number up with the 'ceil' command. Then we divide by the
        % total number of people to get a fractional value of total
        % occupancy, (between zero and 1, naturally) which Energyplus
        % can interpret and multiply by an occupant density to get the
        % right number of people.
        % occout.val(zone,count)  = ceil(mean(Occupancy(ii-
3:ii)))/NumberOfPeople;

        if count==35041; %stop when we get to the end of the year
            break
        end

        count=count+1;

    end % of looping through 34041 occupancy entries

end % of zonal loop
OccProfile=occout.val;

end % of function
```

APPENDIX C: 6-DAY DAYLIGHTING STUDY RESULTS

Calculation of annual footcandle-hours (fc-hrs) using each 2-step and 3-step skies.

MARCH ANALYSIS

South	North
5,847	2,539
4,988	2,221
14.7%	12.5%

2 Clear, 2 Partly Cloudy, 2 Overcast
3 Clear, 3 Overcast

	3-Step	2-Step
21-Mar	1	1
22-Mar	3	2
23-Mar	2	1
24-Mar	3	1
25-Mar	1	2
26-Mar	2	2

DECEMBER ANALYSIS

South	North
11,419	975
13,803	955
20.9%	2.0%

2 Clear, 2 Partly Cloudy, 2 Overcast
3 Clear, 3 Overcast

	3-Step	2-Step
21-Dec	3	2
22-Dec	1	1
23-Dec	1	2
24-Dec	2	2
25-Dec	2	1
26-Dec	3	1

JUNE ANALYSIS

South	North
4,006	2,931
3,063	2,340
23.5%	20.2%

2 Clear, 2 Partly Cloudy, 2 Overcast
3 Clear, 3 Overcast

	3-Step	2-Step
21-Jun	1	2
22-Jun	3	1
23-Jun	2	2
24-Jun	2	1
25-Jun	1	2
26-Jun	3	1

3-Step: 1 = Clear
         2 = Partly Cloudy
         3 = Overcast

2-Step: 1 = Clear
         2 = Overcast

SUMMARY

	South	North
December	20.9%	2.0%
March	14.7%	12.5%
June	23.5%	20.2%

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APPENDIX D: FULL-YEAR DAYLIGHTING STUDY RESULTS

	Total Annual fc-Hours		Total Annual Energy Density	
	North	South	North	South
2-Step	129,100	311,017	0.080	0.112
3-Step	150,119	343,219	0.077	0.112
Difference	14.0%	9.4%	-3.2%	0.2%
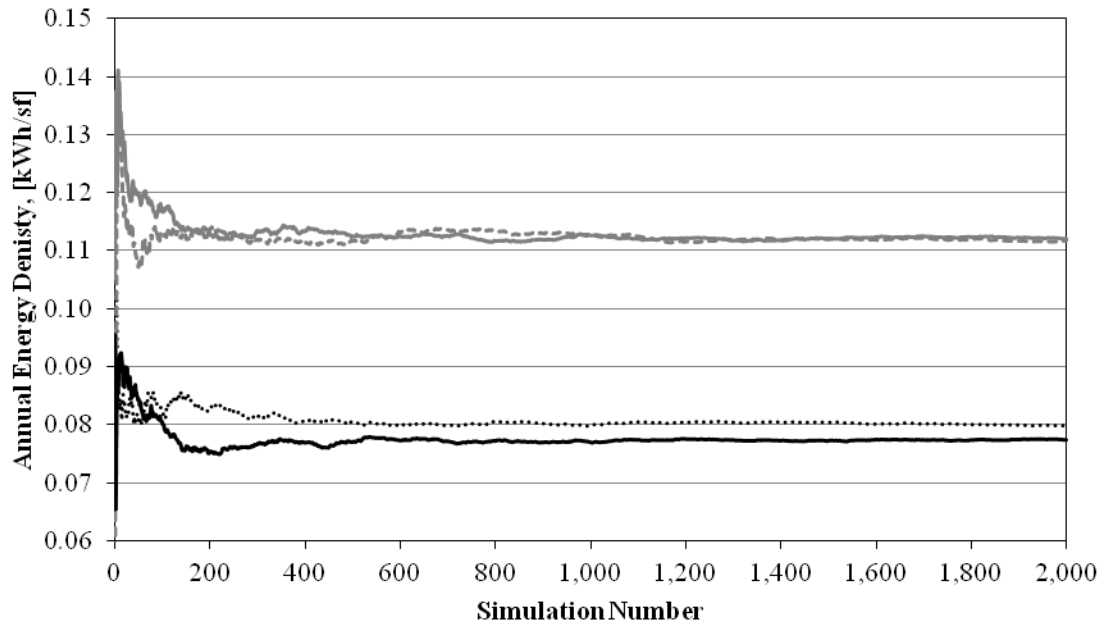
.... North - Without Partly Cloudy	----- South - Without Partly Cloudy	
—— North - With Partly Cloudy	—— South - With Partly Cloudy	

t-Test: Paired Two Sample for Means	SOUTH ENERGY	
	Variable 1	Variable 2
Mean	0.079928	0.077413
Variance	0.000879	0.000773
Observations	2000	2000
Pearson Correlation	-0.00464	
Hypothesized Mean Difference	0	
df	1999	
t Stat	2.761355	
P(T<=t) one-tail	0.002904	
t Critical one-tail	1.645616	
P(T<=t) two-tail	0.005809	
t Critical two-tail	1.961151	

t-Test: Paired Two Sample for Means	NORTH ENERGY	
	Variable 1	*Variable 2*
Mean	0.111872	0.112069
Variance	0.001444	0.001432
Observations	2000	2000
Pearson Correlation	-0.01109	
Hypothesized Mean Difference	0	
df	1999	
t Stat	-0.16327	
P(T<=t) one-tail	0.43516	
t Critical one-tail	1.645616	
P(T<=t) two-tail	0.870319	
t Critical two-tail	1.961151	

APPENDIX E: INITIAL VALIDATION STUDY RESULTS

SUBMETERED DATA: Relative Use Intensity									

DAY:	1	2	3	4	5	6	7	Average	Average
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0.00	0.045	0.046	0.085	0.065	0.085	0.061	0.075	0.068	0.060
1.00	0.045	0.047	0.064	0.057	0.064	0.054	0.060	0.057	0.053
2.00	0.044	0.046	0.054	0.054	0.059	0.052	0.055	0.053	0.049
3.00	0.044	0.047	0.053	0.054	0.058	0.051	0.054	0.053	0.049
4.00	0.042	0.044	0.052	0.053	0.058	0.051	0.055	0.052	0.048
5.00	0.040	0.049	0.056	0.055	0.065	0.055	0.051	0.056	0.046
6.00	0.028	0.070	0.075	0.073	0.094	0.072	0.038	0.077	0.033
7.00	0.018	0.128	0.128	0.127	0.126	0.118	0.029	0.125	0.023
8.00	0.014	0.163	0.163	0.158	0.156	0.154	0.027	0.159	0.021
9.00	0.017	0.167	0.172	0.167	0.164	0.157	0.035	0.165	0.026
10.00	0.023	0.167	0.172	0.165	0.161	0.160	0.040	0.165	0.031
11.00	0.023	0.166	0.167	0.166	0.162	0.154	0.040	0.163	0.032
12.00	0.024	0.155	0.158	0.160	0.152	0.149	0.039	0.155	0.032
13.00	0.028	0.167	0.164	0.162	0.157	0.150	0.037	0.160	0.032
14.00	0.025	0.167	0.166	0.162	0.162	0.152	0.034	0.162	0.029
15.00	0.025	0.167	0.170	0.167	0.162	0.151	0.033	0.163	0.029
16.00	0.026	0.166	0.164	0.163	0.160	0.148	0.035	0.160	0.031
17.00	0.031	0.161	0.159	0.158	0.152	0.140	0.035	0.154	0.033
18.00	0.035	0.150	0.152	0.151	0.147	0.132	0.041	0.146	0.038
19.00	0.038	0.144	0.145	0.148	0.140	0.135	0.044	0.142	0.041
20.00	0.044	0.148	0.141	0.151	0.135	0.140	0.049	0.143	0.047
21.00	0.048	0.136	0.132	0.140	0.121	0.128	0.051	0.131	0.050
22.00	0.049	0.123	0.110	0.118	0.102	0.114	0.047	0.113	0.048
23.00	0.047	0.111	0.083	0.110	0.078	0.097	0.044	0.096	0.045
Annual kWh	537	1,965	1,998	1,998	1,993	1,859	702	11,052	

			SIMULATION SETTINGS: Parameter Set 1	
	On DC		50% = 0, 50% = 1	
	Off DC		All = 0	
	Int On DC		50% = 0, 50% = 1	
	Int Off DC		50% = 0, 50% = 1	
	R or L		All = 0	
	mu		Built-in (randomized)	

SIMULATION RESULTS: Parameter Set 1

Hour	1 Sun	2 Mon	3 Tue	4 Wed	5 Thu	6 Fri	7 Sat	Weekday	Weekend Day
0	0.132	0.005	0.006	0.003	0.006	0.004	0.002	0.005	0.067
1	0.001	0.005	0.006	0.003	0.004	0.004	0.002	0.004	0.001
2	0.001	0.005	0.005	0.003	0.003	0.004	0.002	0.004	0.002
3	0.002	0.005	0.005	0.003	0.003	0.004	0.001	0.004	0.002
4	0.003	0.004	0.004	0.002	0.003	0.004	0.002	0.004	0.002
5	0.003	0.007	0.008	0.007	0.006	0.008	0.002	0.007	0.002
6	0.002	0.059	0.056	0.054	0.052	0.052	0.003	0.055	0.002
7	0.003	0.205	0.191	0.196	0.185	0.185	0.005	0.192	0.004
8	0.006	0.256	0.248	0.239	0.236	0.227	0.008	0.241	0.007
9	0.009	0.270	0.254	0.254	0.250	0.241	0.010	0.254	0.010
10	0.013	0.303	0.282	0.277	0.274	0.254	0.016	0.278	0.015
11	0.013	0.217	0.213	0.196	0.183	0.178	0.020	0.198	0.017
12	0.017	0.204	0.194	0.173	0.139	0.153	0.018	0.173	0.017
13	0.020	0.240	0.235	0.229	0.196	0.220	0.021	0.224	0.020
14	0.020	0.215	0.222	0.224	0.235	0.232	0.023	0.226	0.021
15	0.023	0.199	0.219	0.216	0.225	0.214	0.019	0.214	0.021
16	0.025	0.181	0.189	0.178	0.191	0.187	0.022	0.185	0.024
17	0.026	0.106	0.097	0.099	0.094	0.103	0.021	0.100	0.024
18	0.018	0.041	0.048	0.037	0.040	0.046	0.017	0.042	0.018
19	0.009	0.023	0.031	0.020	0.028	0.023	0.011	0.025	0.010
20	0.008	0.017	0.024	0.014	0.020	0.012	0.009	0.017	0.009
21	0.006	0.011	0.017	0.012	0.014	0.008	0.010	0.012	0.008
22	0.006	0.007	0.010	0.006	0.008	0.004	0.008	0.007	0.007
23	0.004	0.008	0.005	0.008	0.006	0.001	0.005	0.005	0.005
Annual kWh	249	1,738	1,720	1,642	1,637	1,587	172	8,743	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 1	249	1,738	1,720	1,642	1,637	1,587	172	8,743
Error	53.7%	11.6%	13.9%	17.8%	17.9%	14.6%	75.6%	20.89%

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SIMULATION SETTINGS: Parameter Set 2

On DC	All = 0
Off DC	All = 0
Int On DC	All = 0
Int Off DC	All = 0
R or L	All = 0
mu	Built-in (randomized)

SIMULATION RESULTS: Parameter Set 2

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.003	0.002	0.002	0.002	0.001	0.002	0.002	0.002
1	0.003	0.002	0.002	0.003	0.002	0.001	0.002	0.002	0.003
2	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.002
3	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.002
4	0.003	0.005	0.004	0.003	0.004	0.003	0.001	0.004	0.002
5	0.002	0.037	0.032	0.027	0.031	0.035	0.002	0.032	0.002
6	0.002	0.084	0.074	0.081	0.080	0.083	0.003	0.080	0.003
7	0.005	0.082	0.072	0.076	0.081	0.071	0.006	0.076	0.005
8	0.007	0.077	0.066	0.072	0.078	0.074	0.006	0.073	0.007
9	0.006	0.069	0.057	0.063	0.060	0.061	0.008	0.062	0.007
10	0.005	0.036	0.028	0.038	0.032	0.036	0.010	0.034	0.008
11	0.010	0.045	0.038	0.040	0.037	0.038	0.007	0.040	0.008
12	0.010	0.051	0.052	0.052	0.054	0.054	0.008	0.053	0.009
13	0.010	0.038	0.041	0.044	0.044	0.047	0.010	0.043	0.010
14	0.008	0.039	0.043	0.047	0.042	0.037	0.011	0.042	0.010
15	0.008	0.041	0.039	0.040	0.041	0.042	0.011	0.041	0.010
16	0.009	0.026	0.022	0.023	0.022	0.027	0.009	0.024	0.009
17	0.007	0.010	0.016	0.012	0.010	0.016	0.008	0.013	0.007
18	0.005	0.006	0.011	0.009	0.009	0.008	0.005	0.009	0.005
19	0.005	0.006	0.007	0.008	0.008	0.006	0.007	0.007	0.006
20	0.004	0.005	0.006	0.005	0.008	0.006	0.008	0.006	0.006
21	0.004	0.004	0.006	0.004	0.007	0.003	0.003	0.005	0.004
22	0.003	0.004	0.003	0.005	0.004	0.001	0.003	0.004	0.003
23	0.002	0.003	0.002	0.002	0.002	0.001	0.002	0.002	0.002
Annual kWh	183	452	421	442	453	440	91	2,482	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 2	183	452	421	442	453	440	91	2,482
Error	65.9%	77.0%	78.9%	77.9%	77.3%	76.4%	87.1%	77.55%

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SIMULATION SETTINGS: Parameter Set 3	
On DC	50% = 0.5, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.5, 50% = 0
Int Off DC	50% = 0.5, 50% = 0
R or L	All = 0
mu	Built-in (randomized)

SIMULATION RESULTS: Parameter Set 3									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.001	0.001	0.002	0.002	0.003	0.002	0.002	0.002	0.002
1	0.001	0.002	0.001	0.002	0.003	0.001	0.001	0.002	0.001
2	0.002	0.002	0.002	0.003	0.003	0.001	0.001	0.002	0.002
3	0.002	0.002	0.002	0.002	0.002	0.001	0.001	0.002	0.001
4	0.001	0.002	0.001	0.002	0.002	0.001	0.001	0.002	0.001
5	0.002	0.005	0.003	0.004	0.006	0.005	0.002	0.005	0.002
6	0.002	0.040	0.040	0.039	0.037	0.039	0.003	0.039	0.002
7	0.003	0.101	0.094	0.096	0.096	0.100	0.002	0.097	0.003
8	0.004	0.109	0.094	0.096	0.103	0.096	0.005	0.099	0.005
9	0.006	0.103	0.087	0.090	0.093	0.095	0.008	0.094	0.007
10	0.007	0.093	0.077	0.083	0.082	0.085	0.007	0.084	0.007
11	0.006	0.049	0.046	0.048	0.047	0.056	0.008	0.049	0.007
12	0.007	0.061	0.053	0.051	0.053	0.056	0.008	0.055	0.008
13	0.010	0.076	0.068	0.073	0.073	0.074	0.009	0.073	0.010
14	0.011	0.061	0.060	0.060	0.067	0.065	0.010	0.063	0.010
15	0.011	0.059	0.063	0.068	0.062	0.054	0.009	0.061	0.010
16	0.010	0.059	0.058	0.059	0.055	0.050	0.012	0.056	0.011
17	0.011	0.036	0.028	0.033	0.030	0.029	0.010	0.031	0.010
18	0.007	0.012	0.015	0.012	0.016	0.016	0.007	0.014	0.007
19	0.005	0.007	0.013	0.009	0.011	0.009	0.005	0.010	0.005
20	0.004	0.006	0.011	0.007	0.010	0.006	0.005	0.008	0.005
21	0.003	0.005	0.009	0.006	0.008	0.005	0.006	0.007	0.005
22	0.003	0.004	0.006	0.003	0.006	0.003	0.005	0.005	0.004
23	0.002	0.003	0.003	0.003	0.003	0.002	0.002	0.003	0.002
Annual kWh	81	600	560	570	593	571	88	3,064	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 3	81	600	560	570	593	571	88	3,064
Error	84.9%	69.5%	72.0%	71.5%	70.2%	69.3%	87.5%	72.28%

SIMULATION SETTINGS: Parameter Set 4	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 0
mu	Built-in (randomized)

SIMULATION RESULTS: Parameter Set 4									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.003	0.003	0.003	0.003	0.004	0.003	0.002	0.003	0.002
1	0.003	0.005	0.003	0.003	0.004	0.003	0.002	0.003	0.002
2	0.002	0.005	0.002	0.003	0.004	0.003	0.002	0.003	0.002
3	0.002	0.004	0.003	0.004	0.003	0.003	0.002	0.003	0.002
4	0.003	0.005	0.003	0.004	0.004	0.004	0.002	0.004	0.002
5	0.003	0.008	0.007	0.008	0.008	0.007	0.002	0.008	0.002
6	0.003	0.061	0.059	0.059	0.057	0.057	0.003	0.059	0.003
7	0.004	0.165	0.154	0.156	0.157	0.156	0.003	0.157	0.004
8	0.006	0.183	0.170	0.166	0.178	0.162	0.007	0.172	0.007
9	0.009	0.180	0.165	0.165	0.172	0.161	0.009	0.169	0.009
10	0.014	0.177	0.154	0.157	0.161	0.156	0.013	0.161	0.014
11	0.010	0.101	0.090	0.089	0.095	0.096	0.015	0.094	0.012
12	0.017	0.115	0.096	0.095	0.095	0.100	0.015	0.100	0.016
13	0.019	0.141	0.123	0.135	0.134	0.140	0.014	0.134	0.017
14	0.019	0.114	0.109	0.119	0.123	0.125	0.016	0.118	0.018
15	0.018	0.114	0.111	0.119	0.115	0.104	0.018	0.113	0.018
16	0.018	0.110	0.101	0.101	0.100	0.091	0.019	0.101	0.018
17	0.016	0.062	0.054	0.055	0.054	0.050	0.016	0.055	0.016
18	0.012	0.023	0.025	0.023	0.025	0.026	0.012	0.024	0.012
19	0.008	0.012	0.017	0.014	0.018	0.013	0.010	0.015	0.009
20	0.006	0.009	0.014	0.011	0.017	0.008	0.010	0.012	0.008
21	0.005	0.007	0.010	0.009	0.013	0.006	0.008	0.009	0.007
22	0.005	0.006	0.009	0.007	0.010	0.003	0.006	0.007	0.006
23	0.004	0.005	0.006	0.006	0.004	0.002	0.004	0.005	0.004
Annual kWh	143	1,080	996	1,011	1,062	992	140	5,423	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 4	143	1,080	996	1,011	1,062	992	140	5,423
Error	73.4%	45.1%	50.2%	49.4%	46.7%	46.6%	80.1%	50.93%

SIMULATION SETTINGS: Parameter Set 5	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 0
mu	0.028

SIMULATION RESULTS: Parameter Set 5

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.001	0.004	0.003	0.006	0.004	0.001	0.003	0.002
1	0.002	0.002	0.002	0.003	0.005	0.003	0.001	0.003	0.002
2	0.002	0.002	0.003	0.002	0.005	0.004	0.001	0.003	0.001
3	0.002	0.003	0.003	0.002	0.004	0.004	0.001	0.003	0.002
4	0.002	0.003	0.003	0.002	0.004	0.003	0.001	0.003	0.002
5	0.003	0.009	0.008	0.008	0.008	0.007	0.002	0.008	0.002
6	0.002	0.076	0.073	0.070	0.072	0.069	0.002	0.072	0.002
7	0.004	0.185	0.175	0.167	0.174	0.168	0.003	0.174	0.004
8	0.004	0.192	0.157	0.165	0.175	0.162	0.008	0.170	0.006
9	0.005	0.179	0.156	0.159	0.163	0.157	0.009	0.163	0.007
10	0.009	0.170	0.139	0.140	0.145	0.136	0.009	0.146	0.009
11	0.008	0.077	0.068	0.070	0.064	0.065	0.013	0.069	0.011
12	0.012	0.080	0.065	0.066	0.055	0.066	0.011	0.066	0.011
13	0.013	0.105	0.087	0.098	0.093	0.102	0.011	0.097	0.012
14	0.013	0.077	0.076	0.076	0.089	0.086	0.013	0.081	0.013
15	0.012	0.082	0.087	0.083	0.084	0.070	0.011	0.081	0.012
16	0.013	0.069	0.070	0.065	0.060	0.057	0.014	0.064	0.014
17	0.012	0.034	0.030	0.030	0.028	0.024	0.011	0.029	0.012
18	0.009	0.009	0.011	0.014	0.014	0.010	0.010	0.012	0.009
19	0.008	0.006	0.007	0.009	0.015	0.006	0.008	0.009	0.008
20	0.008	0.007	0.007	0.009	0.020	0.006	0.006	0.010	0.007
21	0.006	0.007	0.006	0.010	0.016	0.006	0.005	0.009	0.006
22	0.006	0.004	0.005	0.008	0.010	0.004	0.004	0.006	0.005
23	0.004	0.004	0.003	0.007	0.005	0.001	0.002	0.004	0.003
Annual kWh	107	927	833	847	896	817	108	4,534	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 5	107	927	833	847	896	817	108	4,534
Error	80.0%	52.9%	58.3%	57.6%	55.0%	56.1%	84.6%	58.97%

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SIMULATION SETTINGS: Parameter Set 6	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 0
mu	0.065

SIMULATION RESULTS: Parameter Set 6

	1	2	3	4	5	6	7			
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat		Weekday	Weekend Day
0	0.003	0.003	0.003	0.003	0.005	0.004	0.005		0.004	0.004
1	0.003	0.004	0.003	0.002	0.005	0.002	0.003		0.003	0.003
2	0.003	0.004	0.003	0.003	0.005	0.002	0.003		0.003	0.003
3	0.003	0.004	0.002	0.004	0.005	0.003	0.002		0.004	0.003
4	0.003	0.003	0.003	0.003	0.004	0.003	0.003		0.003	0.003
5	0.004	0.008	0.008	0.006	0.007	0.006	0.004		0.007	0.004
6	0.004	0.055	0.055	0.050	0.052	0.050	0.005		0.052	0.004
7	0.005	0.148	0.136	0.151	0.146	0.135	0.005		0.143	0.005
8	0.008	0.168	0.158	0.159	0.163	0.152	0.008		0.160	0.008
9	0.012	0.180	0.162	0.163	0.155	0.154	0.010		0.163	0.011
10	0.016	0.168	0.139	0.148	0.142	0.137	0.012		0.147	0.014
11	0.012	0.099	0.084	0.083	0.078	0.081	0.016		0.085	0.014
12	0.023	0.102	0.087	0.083	0.074	0.087	0.014		0.086	0.018
13	0.022	0.110	0.106	0.110	0.114	0.118	0.015		0.112	0.018
14	0.021	0.087	0.096	0.097	0.104	0.103	0.020		0.097	0.020
15	0.017	0.086	0.098	0.101	0.088	0.087	0.023		0.092	0.020
16	0.012	0.080	0.083	0.075	0.072	0.073	0.026		0.077	0.019
17	0.012	0.044	0.040	0.039	0.032	0.038	0.019		0.039	0.015
18	0.011	0.015	0.020	0.015	0.017	0.019	0.011		0.017	0.011
19	0.009	0.009	0.013	0.009	0.017	0.008	0.011		0.011	0.010
20	0.007	0.008	0.010	0.011	0.019	0.007	0.009		0.011	0.008
21	0.005	0.008	0.012	0.010	0.019	0.007	0.010		0.011	0.008
22	0.006	0.005	0.013	0.006	0.011	0.005	0.008		0.008	0.007
23	0.004	0.005	0.007	0.006	0.006	0.005	0.005		0.006	0.005
Annual kWh	151	940	898	894	914	860	165		4,822	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 6	151	940	898	894	914	860	165	4,822
Error	71.8%	52.2%	55.1%	55.2%	54.2%	53.7%	76.6%	56.37%

SIMULATION SETTINGS: Parameter Set 7	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 1, 50% = 0
Int Off DC	50% = 0.5, 50% = 0
R or L	All = 0
mu	0.065

SIMULATION RESULTS: Parameter Set 7

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.001	0.002	0.005	0.004	0.003	0.003	0.001	0.004	0.001
1	0.002	0.004	0.003	0.004	0.003	0.003	0.002	0.003	0.002
2	0.001	0.004	0.003	0.005	0.004	0.003	0.002	0.004	0.002
3	0.002	0.004	0.004	0.004	0.003	0.003	0.001	0.004	0.001
4	0.001	0.004	0.004	0.004	0.003	0.003	0.002	0.004	0.002
5	0.002	0.005	0.006	0.006	0.005	0.006	0.001	0.006	0.001
6	0.002	0.043	0.043	0.042	0.040	0.043	0.003	0.042	0.002
7	0.004	0.131	0.133	0.136	0.132	0.133	0.003	0.133	0.003
8	0.005	0.167	0.160	0.148	0.165	0.149	0.008	0.158	0.007
9	0.010	0.175	0.158	0.153	0.167	0.157	0.009	0.162	0.010
10	0.011	0.164	0.137	0.130	0.144	0.146	0.014	0.144	0.012
11	0.011	0.087	0.069	0.067	0.080	0.084	0.016	0.077	0.013
12	0.012	0.090	0.079	0.076	0.076	0.081	0.015	0.080	0.014
13	0.016	0.117	0.105	0.115	0.113	0.108	0.014	0.112	0.015
14	0.016	0.099	0.097	0.104	0.109	0.096	0.016	0.101	0.016
15	0.017	0.090	0.093	0.093	0.102	0.078	0.021	0.091	0.019
16	0.017	0.085	0.084	0.076	0.082	0.066	0.018	0.079	0.018
17	0.017	0.047	0.048	0.038	0.038	0.033	0.018	0.041	0.017
18	0.013	0.020	0.021	0.017	0.018	0.017	0.012	0.019	0.013
19	0.007	0.013	0.015	0.014	0.014	0.011	0.010	0.013	0.009
20	0.008	0.009	0.014	0.009	0.012	0.010	0.008	0.011	0.008
21	0.008	0.008	0.011	0.007	0.010	0.008	0.006	0.009	0.007
22	0.007	0.006	0.009	0.005	0.007	0.005	0.004	0.006	0.005
23	0.004	0.006	0.006	0.004	0.004	0.002	0.002	0.004	0.003
Annual kWh	131	924	874	844	909	836	137	4,655	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 7	131	924	874	844	909	836	137	4,655
Error	75.6%	53.0%	56.2%	57.8%	54.4%	55.0%	80.5%	57.88%

SIMULATION SETTINGS: Parameter Set 8	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 1, 50% = 0
Int Off DC	50% = 0.25, 50% = 0
R or L	All = 0
mu	0.065

SIMULATION RESULTS: Parameter Set 8

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.003	0.003	0.003	0.004	0.002	0.002	0.003	0.002
1	0.001	0.004	0.003	0.002	0.003	0.003	0.002	0.003	0.002
2	0.002	0.003	0.002	0.002	0.003	0.003	0.001	0.003	0.002
3	0.002	0.002	0.001	0.003	0.003	0.003	0.001	0.002	0.002
4	0.002	0.002	0.002	0.003	0.002	0.002	0.002	0.002	0.002
5	0.001	0.005	0.005	0.005	0.004	0.004	0.003	0.005	0.002
6	0.003	0.043	0.039	0.040	0.038	0.038	0.003	0.040	0.003
7	0.004	0.116	0.111	0.112	0.113	0.108	0.004	0.112	0.004
8	0.006	0.105	0.105	0.101	0.108	0.098	0.007	0.103	0.006
9	0.008	0.103	0.091	0.092	0.100	0.100	0.010	0.097	0.009
10	0.012	0.085	0.066	0.071	0.079	0.072	0.012	0.075	0.012
11	0.007	0.034	0.027	0.031	0.032	0.035	0.010	0.032	0.009
12	0.012	0.050	0.042	0.045	0.040	0.042	0.010	0.044	0.011
13	0.013	0.063	0.054	0.062	0.067	0.063	0.009	0.062	0.011
14	0.012	0.039	0.047	0.043	0.055	0.050	0.013	0.047	0.012
15	0.011	0.052	0.049	0.055	0.051	0.039	0.012	0.049	0.012
16	0.010	0.047	0.042	0.044	0.042	0.039	0.016	0.043	0.013
17	0.011	0.020	0.018	0.019	0.021	0.019	0.011	0.020	0.011
18	0.007	0.009	0.011	0.009	0.009	0.013	0.008	0.010	0.007
19	0.005	0.006	0.011	0.008	0.012	0.008	0.009	0.009	0.007
20	0.004	0.006	0.009	0.007	0.011	0.008	0.008	0.008	0.006
21	0.003	0.006	0.009	0.008	0.008	0.004	0.008	0.007	0.006
22	0.005	0.005	0.009	0.004	0.006	0.003	0.006	0.005	0.006
23	0.002	0.005	0.005	0.005	0.004	0.002	0.004	0.004	0.003
Annual kWh	98	546	509	518	558	507	116	2,851	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 8	98	546	509	518	558	507	116	2,851
Error	81.8%	72.2%	74.5%	74.1%	72.0%	72.7%	83.5%	74.21%

		SIMULATION SETTINGS: Parameter Set 9	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 0
mu	0.1

SIMULATION RESULTS: Parameter Set 9

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.004	0.004	0.004	0.005	0.003	0.003	0.004	0.003
1	0.002	0.005	0.002	0.004	0.005	0.004	0.002	0.004	0.002
2	0.002	0.005	0.002	0.003	0.004	0.004	0.003	0.004	0.003
3	0.003	0.004	0.002	0.003	0.003	0.003	0.002	0.003	0.003
4	0.003	0.005	0.003	0.004	0.004	0.003	0.002	0.004	0.003
5	0.003	0.008	0.008	0.009	0.008	0.007	0.003	0.008	0.003
6	0.003	0.064	0.063	0.061	0.056	0.058	0.004	0.060	0.003
7	0.004	0.149	0.150	0.156	0.143	0.145	0.004	0.149	0.004
8	0.006	0.161	0.157	0.154	0.153	0.140	0.007	0.153	0.006
9	0.009	0.162	0.151	0.154	0.155	0.147	0.012	0.154	0.011
10	0.014	0.169	0.145	0.143	0.149	0.150	0.016	0.151	0.015
11	0.013	0.102	0.081	0.085	0.088	0.092	0.018	0.090	0.016
12	0.018	0.108	0.090	0.094	0.089	0.088	0.019	0.094	0.018
13	0.022	0.129	0.104	0.126	0.118	0.118	0.017	0.119	0.019
14	0.021	0.102	0.099	0.112	0.113	0.107	0.019	0.107	0.020
15	0.017	0.104	0.103	0.105	0.099	0.095	0.018	0.101	0.018
16	0.021	0.101	0.086	0.093	0.092	0.081	0.022	0.091	0.022
17	0.019	0.060	0.054	0.051	0.046	0.044	0.018	0.051	0.018
18	0.015	0.024	0.031	0.023	0.027	0.028	0.015	0.027	0.015
19	0.012	0.017	0.021	0.017	0.021	0.015	0.012	0.018	0.012
20	0.009	0.013	0.015	0.011	0.019	0.011	0.011	0.014	0.010
21	0.006	0.009	0.013	0.010	0.013	0.006	0.010	0.010	0.008
22	0.006	0.008	0.011	0.005	0.008	0.005	0.008	0.007	0.007
23	0.005	0.006	0.006	0.005	0.005	0.003	0.005	0.005	0.005
Annual kWh	159	1,016	939	960	970	909	166	5,119	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 9	159	1,016	939	960	970	909	166	5,119
Error	70.4%	48.3%	53.0%	52.0%	51.3%	51.1%	76.3%	53.69%

SIMULATION SETTINGS: Parameter Set 10

On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 0
mu	0.01

SIMULATION RESULTS: Parameter Set 10

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.003	0.004	0.003	0.005	0.004	0.004	0.004	0.003
1	0.002	0.004	0.004	0.002	0.003	0.003	0.004	0.003	0.003
2	0.002	0.004	0.004	0.003	0.004	0.003	0.004	0.004	0.003
3	0.003	0.003	0.003	0.004	0.005	0.004	0.003	0.004	0.003
4	0.003	0.003	0.003	0.004	0.005	0.003	0.003	0.004	0.003
5	0.002	0.007	0.006	0.007	0.007	0.005	0.003	0.006	0.002
6	0.002	0.049	0.046	0.047	0.047	0.044	0.004	0.047	0.003
7	0.006	0.144	0.142	0.144	0.141	0.141	0.006	0.143	0.006
8	0.007	0.164	0.165	0.164	0.164	0.151	0.010	0.162	0.008
9	0.010	0.165	0.154	0.154	0.157	0.156	0.015	0.157	0.012
10	0.017	0.155	0.129	0.135	0.140	0.137	0.018	0.139	0.017
11	0.011	0.086	0.067	0.069	0.069	0.074	0.018	0.073	0.015
12	0.016	0.081	0.065	0.064	0.058	0.065	0.015	0.067	0.015
13	0.018	0.100	0.081	0.086	0.101	0.092	0.014	0.092	0.016
14	0.018	0.076	0.072	0.070	0.097	0.081	0.017	0.079	0.018
15	0.014	0.078	0.072	0.077	0.084	0.063	0.018	0.075	0.016
16	0.013	0.073	0.065	0.063	0.065	0.058	0.019	0.065	0.016
17	0.011	0.036	0.029	0.030	0.031	0.033	0.015	0.032	0.013
18	0.010	0.010	0.016	0.011	0.013	0.015	0.009	0.013	0.010
19	0.008	0.006	0.012	0.007	0.012	0.007	0.009	0.009	0.009
20	0.007	0.006	0.008	0.007	0.013	0.008	0.011	0.008	0.009
21	0.005	0.005	0.009	0.010	0.013	0.007	0.010	0.009	0.007
22	0.005	0.005	0.009	0.007	0.010	0.005	0.006	0.007	0.006
23	0.004	0.006	0.005	0.007	0.006	0.004	0.003	0.006	0.004
Annual kWh	131	848	782	788	853	779	159	4,341	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 10	131	848	782	788	853	779	159	4,341
Error	75.6%	56.8%	60.9%	60.6%	57.2%	58.1%	77.3%	60.73%

SIMULATION SETTINGS: Parameter Set 11

On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 0
mu	0.06

SIMULATION RESULTS: Parameter Set 11

Hour	1 Sun	2 Mon	3 Tue	4 Wed	5 Thu	6 Fri	7 Sat	Weekday	Weekend Day
0	0.001	0.003	0.003	0.002	0.003	0.002	0.001	0.003	0.001
1	0.001	0.003	0.002	0.002	0.002	0.002	0.001	0.002	0.001
2	0.001	0.003	0.002	0.002	0.002	0.002	0.001	0.002	0.001
3	0.001	0.003	0.002	0.002	0.002	0.002	0.001	0.002	0.001
4	0.001	0.003	0.003	0.001	0.003	0.002	0.001	0.002	0.001
5	0.002	0.005	0.006	0.007	0.007	0.006	0.002	0.006	0.002
6	0.002	0.044	0.041	0.044	0.037	0.040	0.002	0.041	0.002
7	0.003	0.112	0.103	0.113	0.107	0.105	0.003	0.108	0.003
8	0.003	0.099	0.092	0.088	0.094	0.088	0.006	0.092	0.005
9	0.006	0.095	0.088	0.089	0.089	0.088	0.007	0.090	0.006
10	0.009	0.085	0.068	0.070	0.073	0.071	0.010	0.073	0.009
11	0.008	0.032	0.026	0.026	0.026	0.031	0.009	0.028	0.009
12	0.009	0.049	0.039	0.042	0.038	0.042	0.010	0.042	0.010
13	0.010	0.058	0.052	0.062	0.059	0.059	0.009	0.058	0.009
14	0.010	0.036	0.041	0.041	0.044	0.044	0.009	0.041	0.009
15	0.009	0.047	0.044	0.049	0.042	0.036	0.011	0.044	0.010
16	0.011	0.045	0.035	0.037	0.036	0.035	0.010	0.038	0.011
17	0.012	0.020	0.018	0.017	0.017	0.018	0.011	0.018	0.012
18	0.009	0.009	0.012	0.008	0.011	0.012	0.008	0.010	0.009
19	0.007	0.007	0.010	0.008	0.011	0.007	0.007	0.009	0.007
20	0.006	0.007	0.008	0.006	0.011	0.006	0.005	0.007	0.005
21	0.004	0.006	0.006	0.006	0.007	0.005	0.005	0.006	0.004
22	0.004	0.004	0.005	0.003	0.005	0.003	0.004	0.004	0.004
23	0.003	0.003	0.003	0.003	0.002	0.001	0.003	0.003	0.003
Annual kWh	89	521	474	486	497	474	90	2,632	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 11	89	521	474	486	497	474	90	2,632
Error	83.4%	73.5%	76.3%	75.7%	75.1%	74.5%	87.2%	76.19%

SIMULATION SETTINGS: Parameter Set 12	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 1
mu	0.1

SIMULATION RESULTS: Parameter Set 12

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.004	0.004	0.004	0.004	0.005	0.004	0.004	0.004	0.004
1	0.003	0.004	0.003	0.004	0.004	0.003	0.003	0.004	0.003
2	0.003	0.004	0.003	0.004	0.004	0.005	0.002	0.004	0.002
3	0.004	0.003	0.002	0.005	0.003	0.004	0.002	0.003	0.003
4	0.003	0.003	0.003	0.004	0.004	0.004	0.004	0.004	0.003
5	0.003	0.007	0.006	0.006	0.006	0.005	0.004	0.006	0.004
6	0.003	0.049	0.047	0.050	0.046	0.043	0.005	0.047	0.004
7	0.006	0.153	0.150	0.151	0.145	0.146	0.006	0.149	0.006
8	0.008	0.182	0.173	0.171	0.173	0.166	0.010	0.173	0.009
9	0.012	0.174	0.163	0.166	0.167	0.169	0.018	0.168	0.015
10	0.020	0.174	0.146	0.151	0.156	0.152	0.019	0.156	0.020
11	0.013	0.105	0.095	0.092	0.089	0.098	0.016	0.096	0.015
12	0.020	0.112	0.105	0.097	0.089	0.095	0.017	0.100	0.019
13	0.025	0.130	0.121	0.127	0.135	0.129	0.017	0.128	0.021
14	0.025	0.099	0.110	0.113	0.125	0.119	0.024	0.113	0.024
15	0.021	0.105	0.107	0.117	0.112	0.103	0.025	0.109	0.023
16	0.019	0.107	0.106	0.107	0.100	0.096	0.029	0.103	0.024
17	0.017	0.066	0.057	0.064	0.062	0.062	0.023	0.062	0.020
18	0.015	0.025	0.034	0.027	0.030	0.037	0.015	0.031	0.015
19	0.011	0.016	0.022	0.016	0.022	0.016	0.014	0.019	0.013
20	0.009	0.011	0.016	0.013	0.020	0.010	0.015	0.014	0.012
21	0.006	0.008	0.015	0.012	0.017	0.007	0.016	0.012	0.011
22	0.008	0.007	0.012	0.008	0.011	0.006	0.010	0.009	0.009
23	0.006	0.007	0.008	0.007	0.006	0.004	0.007	0.006	0.007
Annual kWh	176	1,043	1,011	1,016	1,046	992	205	5,489	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 12	176	1,043	1,011	1,016	1,046	992	205	5,489
Error	67.2%	46.9%	49.4%	49.1%	47.5%	46.6%	70.9%	50.34%

SIMULATION SETTINGS: Parameter Set 13	
On DC	58% = 1, 42% = 0
Off DC	All = 0
Int On DC	58% = 1, 42% = 0
Int Off DC	58% = 1, 42% = 0
R or L	All = 0
mu	0.065

SIMULATION RESULTS: Parameter Set 13

Hour	1 Sun	2 Mon	3 Tue	4 Wed	5 Thu	6 Fri	7 Sat	Weekday	Weekend Day
0	0.005	0.003	0.006	0.003	0.005	0.003	0.004	0.004	0.004
1	0.004	0.004	0.004	0.003	0.004	0.003	0.003	0.004	0.003
2	0.004	0.004	0.004	0.004	0.005	0.003	0.002	0.004	0.003
3	0.004	0.004	0.004	0.004	0.004	0.004	0.002	0.004	0.003
4	0.004	0.004	0.004	0.003	0.003	0.003	0.002	0.003	0.003
5	0.004	0.008	0.010	0.009	0.006	0.005	0.003	0.008	0.004
6	0.005	0.060	0.056	0.060	0.048	0.051	0.004	0.055	0.004
7	0.007	0.175	0.169	0.175	0.158	0.171	0.004	0.169	0.006
8	0.009	0.241	0.228	0.224	0.218	0.200	0.009	0.222	0.009
9	0.018	0.273	0.248	0.257	0.245	0.234	0.014	0.251	0.016
10	0.026	0.303	0.271	0.283	0.268	0.265	0.018	0.278	0.022
11	0.022	0.240	0.214	0.223	0.213	0.216	0.024	0.221	0.023
12	0.031	0.237	0.222	0.213	0.205	0.216	0.025	0.219	0.028
13	0.040	0.284	0.265	0.266	0.259	0.260	0.027	0.267	0.034
14	0.044	0.253	0.265	0.267	0.274	0.252	0.035	0.262	0.039
15	0.036	0.233	0.256	0.258	0.265	0.239	0.041	0.250	0.038
16	0.034	0.226	0.241	0.228	0.240	0.206	0.045	0.228	0.040
17	0.030	0.146	0.150	0.148	0.136	0.129	0.038	0.142	0.034
18	0.022	0.057	0.069	0.061	0.060	0.066	0.025	0.063	0.024
19	0.014	0.029	0.035	0.031	0.039	0.027	0.019	0.032	0.017
20	0.008	0.017	0.023	0.022	0.031	0.016	0.017	0.022	0.012
21	0.006	0.015	0.018	0.016	0.024	0.009	0.018	0.016	0.012
22	0.008	0.010	0.013	0.011	0.019	0.008	0.014	0.012	0.011
23	0.005	0.009	0.008	0.008	0.009	0.006	0.010	0.008	0.008
Annual kWh	262	1,897	1,863	1,860	1,868	1,735	270	9,754	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 13	262	1,897	1,863	1,860	1,868	1,735	270	9,754
Error	51.2%	3.5%	6.8%	6.9%	6.3%	6.7%	61.6%	11.74%

SIMULATION SETTINGS: Parameter Set 14	
On DC	58% = 1, 42% = 0
Off DC	All = 0
Int On DC	58% = 1, 42% = 0
Int Off DC	58% = 1, 42% = 0
R or L	All = 0
mu	0.9

SIMULATION RESULTS: Parameter Set 14

	1	2	3	4	5	6	7			
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat		Weekday	Weekend Day
0	0.004	0.006	0.005	0.003	0.006	0.005	0.005		0.005	0.004
1	0.004	0.006	0.003	0.003	0.005	0.003	0.003		0.004	0.004
2	0.004	0.004	0.004	0.003	0.004	0.003	0.003		0.004	0.003
3	0.003	0.004	0.004	0.003	0.003	0.005	0.003		0.004	0.003
4	0.004	0.004	0.003	0.002	0.003	0.004	0.003		0.003	0.004
5	0.003	0.008	0.006	0.007	0.008	0.008	0.004		0.008	0.004
6	0.005	0.060	0.059	0.054	0.055	0.056	0.004		0.057	0.004
7	0.007	0.195	0.191	0.189	0.176	0.184	0.005		0.187	0.006
8	0.009	0.265	0.263	0.258	0.251	0.236	0.010		0.255	0.010
9	0.015	0.311	0.298	0.294	0.290	0.271	0.017		0.293	0.016
10	0.026	0.351	0.331	0.321	0.313	0.298	0.022		0.323	0.024
11	0.019	0.265	0.264	0.247	0.239	0.248	0.028		0.253	0.024
12	0.032	0.265	0.246	0.226	0.216	0.226	0.030		0.236	0.031
13	0.042	0.316	0.298	0.292	0.294	0.294	0.030		0.299	0.036
14	0.043	0.301	0.308	0.293	0.314	0.301	0.034		0.303	0.039
15	0.035	0.296	0.300	0.287	0.303	0.271	0.040		0.292	0.038
16	0.032	0.273	0.281	0.263	0.274	0.239	0.048		0.266	0.040
17	0.029	0.179	0.171	0.168	0.168	0.150	0.036		0.167	0.033
18	0.021	0.069	0.079	0.073	0.072	0.067	0.024		0.072	0.023
19	0.013	0.034	0.040	0.035	0.039	0.031	0.016		0.036	0.015
20	0.010	0.020	0.029	0.022	0.030	0.018	0.015		0.024	0.012
21	0.008	0.013	0.019	0.016	0.023	0.009	0.013		0.016	0.010
22	0.008	0.010	0.014	0.010	0.017	0.006	0.011		0.011	0.009
23	0.005	0.008	0.008	0.007	0.009	0.004	0.008		0.007	0.007
Annual kWh	255	2,184	2,159	2,060	2,123	1,967	276		11,024	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 14	255	2,184	2,159	2,060	2,123	1,967	276	11,024
Error	52.5%	11.1%	8.0%	3.1%	6.5%	5.8%	60.7%	0.26%

SIMULATION SETTINGS: Parameter Set 15	
On DC	58% = 1, 42% = 0
Off DC	8% = 0.5, 92% = 0
Int On DC	58% = 1, 42% = 0
Int Off DC	58% = 1, 42% = 0
R or L	All = 0
mu	0.9

SIMULATION RESULTS: Parameter Set 15

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.005	0.004	0.004	0.006	0.004	0.002	0.005	0.002
1	0.003	0.004	0.003	0.003	0.004	0.004	0.002	0.004	0.002
2	0.003	0.004	0.003	0.003	0.004	0.005	0.003	0.004	0.003
3	0.003	0.005	0.003	0.003	0.004	0.004	0.002	0.004	0.003
4	0.003	0.005	0.004	0.003	0.004	0.005	0.002	0.004	0.002
5	0.003	0.007	0.007	0.007	0.008	0.008	0.002	0.007	0.003
6	0.003	0.068	0.068	0.072	0.062	0.065	0.003	0.067	0.003
7	0.005	0.213	0.212	0.206	0.198	0.200	0.003	0.206	0.004
8	0.007	0.294	0.285	0.276	0.280	0.261	0.010	0.279	0.008
9	0.011	0.326	0.321	0.309	0.301	0.289	0.012	0.309	0.012
10	0.017	0.357	0.345	0.339	0.328	0.310	0.019	0.336	0.018
11	0.019	0.261	0.258	0.247	0.242	0.242	0.023	0.250	0.021
12	0.023	0.265	0.241	0.234	0.217	0.218	0.025	0.235	0.024
13	0.026	0.324	0.293	0.300	0.291	0.296	0.025	0.301	0.026
14	0.029	0.304	0.305	0.303	0.312	0.299	0.028	0.305	0.029
15	0.031	0.285	0.291	0.282	0.291	0.271	0.030	0.284	0.030
16	0.035	0.261	0.260	0.250	0.251	0.239	0.034	0.252	0.034
17	0.030	0.164	0.158	0.155	0.158	0.148	0.032	0.157	0.031
18	0.023	0.067	0.080	0.070	0.074	0.068	0.023	0.072	0.023
19	0.013	0.032	0.043	0.035	0.043	0.031	0.015	0.037	0.014
20	0.012	0.019	0.032	0.020	0.031	0.016	0.010	0.023	0.011
21	0.009	0.014	0.019	0.015	0.025	0.009	0.010	0.016	0.010
22	0.006	0.007	0.012	0.008	0.015	0.005	0.006	0.010	0.006
23	0.005	0.007	0.007	0.007	0.006	0.003	0.004	0.006	0.004
Annual kWh	215	2,207	2,179	2,110	2,154	2,008	217	11,090	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 15	215	2,207	2,179	2,110	2,154	2,008	217	11,090
Error	60.0%	12.3%	9.1%	5.6%	8.1%	8.0%	69.0%	0.34%

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SIMULATION SETTINGS: Parameter Set 16

On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 1
mu	0.01

SIMULATION RESULTS: Parameter Set 16

	1	2	3	4	5	6	7			
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat		Weekday	Weekend Day
0	0.006	0.003	0.008	0.007	0.009	0.006	0.006		0.007	0.006
1	0.006	0.005	0.007	0.006	0.008	0.005	0.005		0.006	0.006
2	0.007	0.005	0.007	0.007	0.009	0.006	0.005		0.007	0.006
3	0.007	0.005	0.007	0.008	0.010	0.007	0.006		0.007	0.007
4	0.007	0.005	0.007	0.009	0.010	0.007	0.006		0.007	0.007
5	0.007	0.009	0.010	0.013	0.012	0.009	0.006		0.011	0.007
6	0.007	0.061	0.056	0.060	0.062	0.055	0.007		0.059	0.007
7	0.010	0.191	0.178	0.189	0.185	0.180	0.009		0.184	0.009
8	0.012	0.253	0.242	0.248	0.249	0.226	0.014		0.244	0.013
9	0.017	0.278	0.272	0.270	0.269	0.258	0.021		0.270	0.019
10	0.028	0.305	0.291	0.290	0.284	0.273	0.028		0.289	0.028
11	0.023	0.235	0.227	0.225	0.207	0.214	0.034		0.222	0.028
12	0.031	0.235	0.232	0.222	0.195	0.200	0.033		0.217	0.032
13	0.042	0.281	0.282	0.270	0.267	0.253	0.033		0.270	0.037
14	0.046	0.253	0.283	0.266	0.287	0.258	0.039		0.269	0.043
15	0.040	0.240	0.264	0.261	0.269	0.240	0.040		0.255	0.040
16	0.035	0.234	0.244	0.234	0.240	0.220	0.044		0.234	0.039
17	0.027	0.152	0.155	0.144	0.142	0.144	0.034		0.147	0.031
18	0.023	0.057	0.075	0.058	0.061	0.068	0.021		0.064	0.022
19	0.016	0.029	0.039	0.027	0.037	0.026	0.017		0.032	0.017
20	0.014	0.020	0.028	0.020	0.030	0.017	0.019		0.023	0.017
21	0.011	0.014	0.021	0.019	0.026	0.011	0.019		0.018	0.015
22	0.010	0.012	0.019	0.013	0.019	0.008	0.017		0.014	0.014
23	0.007	0.011	0.013	0.013	0.010	0.007	0.011		0.011	0.009
Annual kWh	295	1,937	1,986	1,929	1,975	1,806	319		10,247	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 16	295	1,937	1,986	1,929	1,975	1,806	319	10,247
Error	45.1%	1.4%	0.6%	3.5%	0.9%	2.8%	54.6%	7.28%

SIMULATION SETTINGS: Parameter Set 17	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0.1
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 1
mu	0.01

	SIMULATION RESULTS: Parameter Set 17								
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.004	0.001	0.005	0.005	0.010	0.007	0.003	0.006	0.004
1	0.004	0.003	0.005	0.005	0.011	0.006	0.003	0.006	0.004
2	0.004	0.005	0.005	0.006	0.012	0.006	0.003	0.007	0.004
3	0.005	0.005	0.005	0.006	0.011	0.007	0.002	0.007	0.004
4	0.006	0.006	0.005	0.007	0.013	0.007	0.003	0.008	0.004
5	0.007	0.008	0.009	0.012	0.016	0.011	0.003	0.011	0.005
6	0.006	0.058	0.057	0.069	0.065	0.062	0.003	0.062	0.005
7	0.007	0.206	0.187	0.202	0.194	0.178	0.005	0.193	0.006
8	0.010	0.264	0.242	0.251	0.240	0.218	0.011	0.243	0.011
9	0.016	0.292	0.269	0.265	0.260	0.240	0.013	0.265	0.015
10	0.025	0.314	0.300	0.295	0.290	0.273	0.016	0.295	0.020
11	0.021	0.226	0.222	0.205	0.211	0.214	0.021	0.216	0.021
12	0.031	0.239	0.190	0.189	0.180	0.193	0.017	0.198	0.024
13	0.038	0.292	0.230	0.243	0.231	0.249	0.020	0.249	0.029
14	0.034	0.267	0.238	0.246	0.244	0.244	0.023	0.248	0.028
15	0.027	0.255	0.228	0.237	0.237	0.215	0.027	0.234	0.027
16	0.028	0.227	0.209	0.204	0.214	0.195	0.030	0.210	0.029
17	0.024	0.127	0.126	0.116	0.121	0.117	0.027	0.121	0.026
18	0.016	0.050	0.056	0.048	0.052	0.056	0.020	0.052	0.018
19	0.010	0.028	0.028	0.028	0.028	0.020	0.016	0.026	0.013
20	0.009	0.017	0.019	0.021	0.020	0.010	0.015	0.017	0.012
21	0.008	0.012	0.016	0.016	0.018	0.007	0.011	0.014	0.010
22	0.009	0.009	0.014	0.014	0.014	0.005	0.010	0.011	0.009
23	0.006	0.009	0.007	0.013	0.009	0.004	0.008	0.009	0.007
Annual kWh	237	1,956	1,790	1,809	1,844	1,704	207	9,545	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 17	237	1,956	1,790	1,809	1,844	1,704	207	9,545
Error	55.9%	0.5%	10.4%	9.5%	7.5%	8.3%	70.5%	13.63%

SIMULATION SETTINGS: Parameter Set 18	
On DC	50% = 0.72, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.74, 50% = 0
Int Off DC	50% = 0.74, 50% = 0
R or L	All = 1
mu	0.01

SIMULATION RESULTS: Parameter Set 18

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.003	0.003	0.006	0.004	0.005	0.003	0.003	0.004	0.003
1	0.002	0.004	0.002	0.002	0.004	0.003	0.002	0.003	0.002
2	0.002	0.004	0.004	0.004	0.003	0.003	0.002	0.004	0.002
3	0.003	0.004	0.004	0.003	0.003	0.004	0.002	0.004	0.002
4	0.004	0.004	0.004	0.003	0.003	0.003	0.002	0.003	0.003
5	0.004	0.008	0.010	0.009	0.008	0.007	0.003	0.009	0.003
6	0.003	0.071	0.073	0.069	0.063	0.067	0.004	0.069	0.003
7	0.008	0.179	0.172	0.181	0.171	0.177	0.004	0.176	0.006
8	0.006	0.182	0.166	0.163	0.178	0.166	0.008	0.171	0.007
9	0.009	0.182	0.157	0.160	0.167	0.159	0.010	0.165	0.009
10	0.013	0.172	0.143	0.151	0.152	0.145	0.011	0.153	0.012
11	0.010	0.090	0.078	0.079	0.075	0.074	0.017	0.079	0.014
12	0.014	0.078	0.066	0.070	0.068	0.068	0.013	0.070	0.013
13	0.014	0.094	0.085	0.099	0.106	0.103	0.013	0.098	0.013
14	0.015	0.071	0.076	0.079	0.099	0.091	0.015	0.083	0.015
15	0.015	0.074	0.086	0.091	0.088	0.072	0.015	0.082	0.015
16	0.016	0.071	0.067	0.068	0.070	0.069	0.018	0.069	0.017
17	0.017	0.042	0.035	0.033	0.035	0.038	0.016	0.037	0.017
18	0.010	0.016	0.020	0.013	0.019	0.023	0.012	0.018	0.011
19	0.008	0.013	0.014	0.011	0.015	0.011	0.011	0.013	0.009
20	0.008	0.014	0.010	0.010	0.008	0.009	0.013	0.010	0.010
21	0.007	0.010	0.009	0.009	0.007	0.008	0.012	0.009	0.009
22	0.007	0.006	0.008	0.005	0.009	0.004	0.008	0.006	0.008
23	0.005	0.007	0.006	0.006	0.006	0.002	0.004	0.005	0.005
Annual kWh	135	936	872	884	929	877	145	4,779	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 18	135	936	872	884	929	877	145	4,779
Error	74.8%	52.4%	56.4%	55.7%	53.4%	52.8%	79.3%	56.76%

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SIMULATION SETTINGS: Parameter Set 19	
On DC	50% = 0.78, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.76, 50% = 0
Int Off DC	50% = 0.72, 50% = 0
R or L	All = 0
mu	0.01

SIMULATION RESULTS: Parameter Set 19									
	1	**2**	**3**	**4**	**5**	**6**	**7**		
Hour	**Sun**	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Weekday**	**Weekend Day**
0	0.002	0.003	0.004	0.003	0.005	0.003	0.004	0.004	0.003
1	0.002	0.004	0.004	0.002	0.003	0.002	0.004	0.003	0.003
2	0.002	0.004	0.004	0.003	0.004	0.003	0.003	0.003	0.003
3	0.003	0.003	0.003	0.004	0.005	0.003	0.002	0.003	0.002
4	0.002	0.003	0.003	0.004	0.005	0.003	0.002	0.003	0.002
5	0.001	0.007	0.005	0.007	0.006	0.005	0.003	0.006	0.002
6	0.002	0.048	0.046	0.046	0.046	0.044	0.003	0.046	0.003
7	0.006	0.142	0.140	0.142	0.139	0.139	0.005	0.140	0.006
8	0.006	0.161	0.160	0.159	0.158	0.146	0.010	0.157	0.008
9	0.010	0.159	0.147	0.149	0.151	0.150	0.014	0.151	0.012
10	0.017	0.147	0.120	0.129	0.134	0.128	0.017	0.132	0.017
11	0.011	0.078	0.061	0.063	0.065	0.067	0.018	0.067	0.014
12	0.015	0.074	0.061	0.058	0.054	0.060	0.014	0.061	0.015
13	0.017	0.092	0.076	0.080	0.096	0.088	0.013	0.086	0.015
14	0.017	0.069	0.066	0.065	0.091	0.075	0.016	0.073	0.017
15	0.014	0.074	0.067	0.073	0.078	0.058	0.017	0.070	0.015
16	0.012	0.068	0.060	0.060	0.061	0.055	0.019	0.061	0.016
17	0.011	0.033	0.026	0.029	0.028	0.030	0.014	0.029	0.013
18	0.010	0.009	0.013	0.010	0.013	0.014	0.009	0.012	0.009
19	0.007	0.005	0.011	0.007	0.012	0.007	0.009	0.008	0.008
20	0.007	0.006	0.008	0.007	0.013	0.008	0.011	0.008	0.009
21	0.005	0.005	0.009	0.010	0.013	0.007	0.009	0.009	0.007
22	0.005	0.004	0.008	0.006	0.009	0.005	0.006	0.007	0.005
23	0.004	0.005	0.005	0.007	0.005	0.004	0.003	0.005	0.003
Annual kWh	125	805	740	751	815	741	151	4,127	

	Sun	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Total Annual**
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 19	125	805	740	751	815	741	151	4,127
Error	76.6%	59.1%	63.0%	62.4%	59.1%	60.2%	78.6%	62.66%

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SIMULATION SETTINGS: Parameter Set 20	
On DC	50% = 0, 7% = 1, 7% = 0.8, 36% = 0.77
Off DC	All = 0
Int On DC	50% = 0, 7% = 1, 7% = 0.8, 36% = 0.72
Int Off DC	50% = 0, 7% = 1, 7% = 0.8, 36% = 0.79
R or L	All = 1
mu	0.01

				SIMULATION RESULTS: Parameter Set 20					
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.003	0.004	0.003	0.006	0.004	0.004	0.004	0.003
1	0.003	0.003	0.003	0.003	0.006	0.004	0.003	0.004	0.003
2	0.004	0.003	0.004	0.004	0.005	0.004	0.002	0.004	0.003
3	0.003	0.002	0.004	0.004	0.006	0.004	0.003	0.004	0.003
4	0.003	0.003	0.004	0.003	0.006	0.005	0.003	0.004	0.003
5	0.003	0.008	0.009	0.009	0.008	0.008	0.003	0.008	0.003
6	0.004	0.057	0.056	0.054	0.048	0.053	0.004	0.054	0.004
7	0.006	0.145	0.148	0.154	0.139	0.150	0.003	0.147	0.005
8	0.007	0.174	0.176	0.176	0.169	0.163	0.007	0.172	0.007
9	0.010	0.184	0.176	0.182	0.173	0.160	0.009	0.175	0.010
10	0.017	0.192	0.172	0.172	0.158	0.159	0.014	0.170	0.015
11	0.015	0.107	0.108	0.108	0.091	0.093	0.014	0.101	0.014
12	0.019	0.105	0.106	0.099	0.082	0.086	0.016	0.096	0.018
13	0.020	0.126	0.127	0.132	0.127	0.131	0.016	0.129	0.018
14	0.019	0.098	0.117	0.117	0.128	0.121	0.020	0.116	0.019
15	0.015	0.091	0.116	0.116	0.114	0.099	0.019	0.107	0.017
16	0.013	0.085	0.088	0.088	0.089	0.088	0.021	0.088	0.017
17	0.012	0.047	0.047	0.049	0.051	0.049	0.016	0.049	0.014
18	0.010	0.023	0.025	0.023	0.025	0.023	0.013	0.024	0.012
19	0.008	0.016	0.018	0.017	0.018	0.013	0.010	0.016	0.009
20	0.009	0.011	0.009	0.013	0.016	0.010	0.010	0.012	0.009
21	0.008	0.009	0.010	0.012	0.015	0.006	0.009	0.010	0.009
22	0.008	0.007	0.007	0.009	0.013	0.004	0.008	0.008	0.008
23	0.004	0.006	0.005	0.009	0.007	0.004	0.005	0.006	0.005
Annual kWh	149	1,007	1,031	1,042	1,023	965	156	5,373	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 20	149	1,007	1,031	1,042	1,023	965	156	5,373
Error	72.1%	48.8%	48.4%	47.8%	48.7%	48.1%	77.7%	51.39%

SIMULATION SETTINGS: Parameter Set 21

On DC	50% = 0.98, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.99, 50% = 0
Int Off DC	50% = 0.92, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 21

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.004	0.004	0.006	0.005	0.005	0.005	0.004	0.005	0.004
1	0.004	0.005	0.004	0.003	0.004	0.004	0.004	0.004	0.004
2	0.003	0.005	0.003	0.003	0.005	0.005	0.004	0.004	0.004
3	0.003	0.003	0.002	0.004	0.005	0.003	0.003	0.004	0.003
4	0.004	0.004	0.002	0.005	0.005	0.003	0.003	0.004	0.003
5	0.004	0.007	0.006	0.008	0.008	0.007	0.004	0.007	0.004
6	0.006	0.050	0.050	0.048	0.049	0.047	0.006	0.049	0.006
7	0.009	0.157	0.158	0.157	0.151	0.157	0.007	0.156	0.008
8	0.013	0.200	0.197	0.202	0.193	0.183	0.012	0.195	0.012
9	0.016	0.209	0.206	0.206	0.205	0.200	0.018	0.205	0.017
10	0.025	0.221	0.198	0.199	0.205	0.194	0.024	0.203	0.025
11	0.018	0.153	0.138	0.132	0.125	0.132	0.026	0.136	0.022
12	0.028	0.149	0.133	0.122	0.114	0.120	0.022	0.128	0.025
13	0.035	0.174	0.156	0.154	0.165	0.158	0.024	0.161	0.030
14	0.035	0.143	0.148	0.143	0.165	0.149	0.030	0.150	0.032
15	0.028	0.139	0.145	0.145	0.150	0.135	0.030	0.143	0.029
16	0.024	0.130	0.133	0.124	0.129	0.123	0.036	0.128	0.030
17	0.022	0.080	0.075	0.073	0.068	0.077	0.025	0.075	0.023
18	0.017	0.027	0.038	0.029	0.029	0.038	0.016	0.032	0.017
19	0.011	0.014	0.021	0.016	0.025	0.015	0.015	0.018	0.013
20	0.011	0.011	0.014	0.013	0.021	0.012	0.017	0.014	0.014
21	0.008	0.010	0.015	0.013	0.019	0.008	0.016	0.013	0.012
22	0.007	0.009	0.014	0.009	0.015	0.004	0.012	0.010	0.010
23	0.005	0.008	0.008	0.008	0.009	0.004	0.007	0.007	0.006
Annual kWh	229	1,280	1,252	1,218	1,273	1,194	243	6,689	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 21	229	1,280	1,252	1,218	1,273	1,194	243	6,689
Error	57.3%	34.9%	37.3%	39.0%	36.1%	35.8%	65.4%	39.48%

SIMULATION SETTINGS: Parameter Set 22	
On DC	50% = 0.75, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.75, 50% = 0
Int Off DC	50% = 0.75, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 22									
	1	**2**	**3**	**4**	**5**	**6**	**7**		
Hour	**Sun**	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Weekday**	**Weekend Day**
0	0.003	0.002	0.002	0.003	0.005	0.004	0.002	0.003	0.002
1	0.003	0.003	0.003	0.002	0.005	0.004	0.003	0.003	0.003
2	0.002	0.004	0.003	0.003	0.004	0.003	0.003	0.003	0.003
3	0.002	0.004	0.003	0.003	0.004	0.003	0.002	0.003	0.002
4	0.003	0.004	0.003	0.003	0.004	0.003	0.002	0.003	0.003
5	0.003	0.005	0.004	0.006	0.006	0.004	0.002	0.005	0.003
6	0.003	0.035	0.034	0.033	0.029	0.032	0.003	0.033	0.003
7	0.004	0.134	0.125	0.127	0.130	0.122	0.003	0.128	0.004
8	0.005	0.152	0.150	0.150	0.147	0.133	0.007	0.146	0.006
9	0.008	0.165	0.149	0.153	0.152	0.142	0.009	0.152	0.009
10	0.013	0.174	0.144	0.145	0.143	0.137	0.011	0.149	0.012
11	0.011	0.090	0.078	0.078	0.078	0.088	0.014	0.082	0.012
12	0.017	0.083	0.069	0.071	0.064	0.069	0.014	0.071	0.016
13	0.021	0.110	0.093	0.098	0.091	0.097	0.017	0.098	0.019
14	0.019	0.082	0.080	0.082	0.089	0.084	0.016	0.083	0.017
15	0.018	0.080	0.076	0.082	0.082	0.069	0.018	0.078	0.018
16	0.016	0.068	0.064	0.067	0.070	0.059	0.020	0.065	0.018
17	0.014	0.035	0.034	0.036	0.033	0.037	0.016	0.035	0.015
18	0.013	0.022	0.020	0.018	0.022	0.023	0.012	0.021	0.012
19	0.010	0.017	0.012	0.013	0.020	0.013	0.010	0.015	0.010
20	0.009	0.011	0.011	0.010	0.021	0.009	0.010	0.012	0.009
21	0.008	0.011	0.013	0.010	0.017	0.006	0.010	0.011	0.009
22	0.007	0.007	0.010	0.007	0.011	0.005	0.009	0.008	0.008
23	0.005	0.004	0.006	0.007	0.007	0.002	0.006	0.005	0.005
Annual kWh	147	871	795	808	841	769	145	4,376	

	Sun	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Total Annual**
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 22	147	871	795	808	841	769	145	4,376
Error	72.7%	55.7%	60.2%	59.6%	57.8%	58.6%	79.3%	60.41%

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SIMULATION SETTINGS: Parameter Set 23

On DC	50% = 0.81, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.76, 50% = 0
Int Off DC	50% = 0.93, 50% = 0
R or L	All = 1
mu	0.01

SIMULATION RESULTS: Parameter Set 23

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.004	0.001	0.007	0.006	0.011	0.002	0.004	0.005	0.004
1	0.003	0.003	0.005	0.005	0.009	0.001	0.003	0.005	0.003
2	0.004	0.004	0.005	0.004	0.007	0.002	0.003	0.004	0.004
3	0.004	0.003	0.006	0.005	0.008	0.003	0.003	0.005	0.004
4	0.003	0.003	0.005	0.004	0.007	0.003	0.003	0.004	0.003
5	0.003	0.008	0.009	0.008	0.011	0.005	0.004	0.008	0.003
6	0.003	0.050	0.050	0.045	0.046	0.044	0.006	0.047	0.005
7	0.006	0.157	0.152	0.144	0.150	0.138	0.008	0.148	0.007
8	0.009	0.210	0.205	0.193	0.202	0.186	0.013	0.199	0.011
9	0.015	0.222	0.217	0.206	0.212	0.199	0.015	0.211	0.015
10	0.022	0.228	0.218	0.202	0.211	0.194	0.020	0.211	0.021
11	0.018	0.142	0.148	0.138	0.129	0.124	0.021	0.136	0.020
12	0.029	0.137	0.140	0.131	0.120	0.117	0.022	0.129	0.026
13	0.034	0.178	0.171	0.172	0.168	0.172	0.023	0.172	0.029
14	0.034	0.161	0.163	0.171	0.177	0.167	0.027	0.168	0.031
15	0.029	0.152	0.150	0.165	0.158	0.145	0.027	0.154	0.028
16	0.022	0.144	0.140	0.141	0.134	0.126	0.034	0.137	0.028
17	0.021	0.093	0.085	0.084	0.076	0.077	0.030	0.083	0.025
18	0.017	0.032	0.036	0.035	0.036	0.035	0.020	0.035	0.018
19	0.011	0.014	0.023	0.019	0.027	0.015	0.016	0.020	0.014
20	0.008	0.013	0.021	0.018	0.023	0.013	0.015	0.017	0.011
21	0.007	0.013	0.017	0.019	0.016	0.009	0.015	0.015	0.011
22	0.006	0.012	0.015	0.014	0.013	0.007	0.012	0.012	0.009
23	0.004	0.012	0.009	0.013	0.007	0.005	0.008	0.009	0.006
Annual kWh	210	1,332	1,337	1,300	1,336	1,197	236	6,949	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 23	210	1,332	1,337	1,300	1,336	1,197	236	6,949
Error	60.8%	32.2%	33.1%	34.9%	33.0%	35.6%	66.4%	37.13%

SIMULATION SETTINGS: Parameter Set 24	
On DC	50% = 0.77, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.76, 50% = 0
Int Off DC	50% = 0.81, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 24

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.002	0.004	0.004	0.007	0.004	0.002	0.004	0.002
1	0.002	0.003	0.003	0.005	0.006	0.003	0.002	0.004	0.002
2	0.002	0.004	0.005	0.005	0.006	0.005	0.002	0.005	0.002
3	0.002	0.004	0.004	0.004	0.005	0.006	0.001	0.005	0.002
4	0.002	0.003	0.004	0.003	0.005	0.005	0.001	0.004	0.002
5	0.002	0.009	0.006	0.008	0.008	0.007	0.002	0.008	0.002
6	0.002	0.055	0.052	0.050	0.052	0.051	0.002	0.052	0.002
7	0.003	0.167	0.158	0.163	0.161	0.153	0.003	0.160	0.003
8	0.003	0.193	0.186	0.181	0.185	0.175	0.005	0.184	0.004
9	0.005	0.196	0.180	0.183	0.184	0.178	0.007	0.184	0.006
10	0.010	0.185	0.172	0.171	0.166	0.167	0.010	0.172	0.010
11	0.008	0.099	0.093	0.092	0.085	0.091	0.015	0.092	0.011
12	0.012	0.098	0.081	0.079	0.068	0.079	0.013	0.081	0.012
13	0.017	0.120	0.109	0.121	0.119	0.124	0.010	0.119	0.013
14	0.017	0.100	0.096	0.112	0.119	0.112	0.013	0.108	0.015
15	0.015	0.093	0.096	0.109	0.104	0.090	0.017	0.099	0.016
16	0.014	0.089	0.082	0.080	0.081	0.070	0.017	0.080	0.016
17	0.014	0.047	0.045	0.044	0.042	0.036	0.016	0.043	0.015
18	0.009	0.021	0.024	0.023	0.025	0.020	0.014	0.023	0.011
19	0.008	0.012	0.015	0.016	0.020	0.009	0.008	0.014	0.008
20	0.008	0.009	0.011	0.013	0.018	0.007	0.006	0.012	0.007
21	0.007	0.008	0.009	0.012	0.015	0.006	0.006	0.010	0.006
22	0.007	0.005	0.009	0.011	0.010	0.003	0.005	0.008	0.006
23	0.005	0.004	0.005	0.010	0.005	0.002	0.003	0.005	0.004
Annual kWh	116	1,023	971	1,004	1,019	940	119	5,192	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 24	116	1,023	971	1,004	1,019	940	119	5,192
Error	78.4%	48.0%	51.4%	49.8%	48.9%	49.4%	83.0%	53.02%

SIMULATION SETTINGS: Parameter Set 25

On DC	50% = 0.77, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.72, 50% = 0
Int Off DC	50% = 0.81, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 25

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.004	0.004	0.005	0.006	0.006	0.002	0.005	0.002
1	0.002	0.005	0.003	0.003	0.004	0.004	0.002	0.004	0.002
2	0.002	0.006	0.003	0.003	0.004	0.003	0.002	0.004	0.002
3	0.004	0.004	0.002	0.004	0.004	0.003	0.002	0.003	0.003
4	0.004	0.004	0.002	0.003	0.006	0.003	0.002	0.003	0.003
5	0.004	0.009	0.007	0.007	0.008	0.007	0.002	0.008	0.003
6	0.004	0.061	0.056	0.057	0.058	0.052	0.004	0.057	0.004
7	0.005	0.177	0.163	0.170	0.165	0.162	0.005	0.167	0.005
8	0.007	0.189	0.185	0.176	0.174	0.168	0.008	0.178	0.007
9	0.012	0.193	0.181	0.180	0.175	0.167	0.011	0.179	0.011
10	0.018	0.195	0.175	0.173	0.167	0.169	0.014	0.176	0.016
11	0.013	0.104	0.101	0.089	0.087	0.090	0.015	0.094	0.014
12	0.022	0.110	0.099	0.091	0.086	0.085	0.015	0.094	0.019
13	0.026	0.133	0.115	0.123	0.126	0.121	0.016	0.124	0.021
14	0.026	0.096	0.101	0.114	0.121	0.107	0.016	0.108	0.021
15	0.020	0.099	0.102	0.118	0.109	0.093	0.019	0.104	0.019
16	0.021	0.087	0.091	0.093	0.087	0.082	0.023	0.088	0.022
17	0.020	0.051	0.048	0.050	0.045	0.046	0.019	0.048	0.019
18	0.014	0.020	0.025	0.023	0.023	0.022	0.014	0.023	0.014
19	0.008	0.011	0.018	0.015	0.018	0.012	0.010	0.015	0.009
20	0.007	0.011	0.013	0.011	0.017	0.011	0.008	0.013	0.008
21	0.006	0.009	0.013	0.010	0.013	0.009	0.009	0.011	0.008
22	0.008	0.007	0.009	0.008	0.010	0.005	0.008	0.008	0.008
23	0.006	0.005	0.007	0.007	0.008	0.004	0.005	0.006	0.005
Annual kWh	174	1,063	1,021	1,026	1,037	958	156	5,434	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 25	174	1,063	1,021	1,026	1,037	958	156	5,434
Error	67.6%	45.9%	48.9%	48.6%	48.0%	48.5%	77.8%	50.83%

SIMULATION SETTINGS: Parameter Set 26	
On DC	50% = 0.74, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.81, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 26

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.004	0.004	0.006	0.003	0.005	0.004	0.004	0.004	0.004
1	0.003	0.005	0.004	0.003	0.004	0.003	0.004	0.004	0.003
2	0.002	0.005	0.005	0.004	0.004	0.003	0.003	0.004	0.003
3	0.003	0.005	0.004	0.004	0.004	0.004	0.003	0.004	0.003
4	0.003	0.004	0.004	0.004	0.004	0.004	0.003	0.004	0.003
5	0.003	0.009	0.010	0.012	0.011	0.008	0.002	0.010	0.003
6	0.004	0.060	0.066	0.065	0.060	0.052	0.004	0.061	0.004
7	0.007	0.161	0.167	0.156	0.149	0.146	0.004	0.156	0.005
8	0.010	0.184	0.183	0.182	0.180	0.161	0.008	0.178	0.009
9	0.013	0.185	0.173	0.175	0.174	0.164	0.009	0.174	0.011
10	0.016	0.174	0.169	0.161	0.167	0.156	0.014	0.165	0.015
11	0.013	0.102	0.100	0.088	0.094	0.087	0.018	0.094	0.015
12	0.018	0.096	0.094	0.080	0.077	0.082	0.015	0.086	0.017
13	0.023	0.123	0.121	0.113	0.109	0.116	0.015	0.116	0.019
14	0.021	0.106	0.099	0.102	0.104	0.101	0.017	0.103	0.019
15	0.016	0.106	0.098	0.110	0.099	0.093	0.018	0.101	0.017
16	0.018	0.099	0.084	0.088	0.086	0.078	0.025	0.087	0.021
17	0.016	0.057	0.048	0.044	0.043	0.041	0.019	0.046	0.018
18	0.012	0.019	0.024	0.019	0.020	0.024	0.015	0.021	0.014
19	0.008	0.012	0.017	0.011	0.016	0.014	0.013	0.014	0.010
20	0.007	0.011	0.013	0.009	0.014	0.009	0.012	0.011	0.009
21	0.007	0.010	0.012	0.011	0.013	0.008	0.011	0.011	0.009
22	0.006	0.007	0.010	0.009	0.012	0.006	0.009	0.009	0.007
23	0.004	0.008	0.005	0.009	0.007	0.004	0.006	0.007	0.005
Annual kWh	159	1,039	1,014	980	994	916	168	5,271	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 26	159	1,039	1,014	980	994	916	168	5,271
Error	70.3%	47.2%	49.2%	51.0%	50.1%	50.7%	76.0%	52.31%

SIMULATION SETTINGS: Parameter Set 27

On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.76, 50% = 0
Int Off DC	50% = 0.68, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 27

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.002	0.004	0.004	0.007	0.003	0.002	0.004	0.002
1	0.002	0.003	0.004	0.003	0.005	0.004	0.002	0.004	0.002
2	0.002	0.003	0.005	0.003	0.006	0.005	0.002	0.004	0.002
3	0.002	0.005	0.004	0.004	0.004	0.006	0.001	0.005	0.002
4	0.001	0.004	0.003	0.005	0.005	0.006	0.002	0.005	0.002
5	0.003	0.007	0.006	0.007	0.006	0.006	0.002	0.006	0.002
6	0.002	0.056	0.058	0.051	0.051	0.051	0.003	0.053	0.002
7	0.004	0.161	0.149	0.147	0.145	0.154	0.002	0.151	0.003
8	0.006	0.180	0.161	0.170	0.170	0.158	0.006	0.168	0.006
9	0.009	0.165	0.159	0.168	0.170	0.155	0.009	0.163	0.009
10	0.011	0.160	0.140	0.148	0.146	0.137	0.010	0.146	0.010
11	0.009	0.076	0.073	0.075	0.070	0.075	0.012	0.074	0.011
12	0.012	0.076	0.076	0.078	0.057	0.070	0.010	0.071	0.011
13	0.012	0.107	0.097	0.113	0.107	0.102	0.009	0.105	0.011
14	0.015	0.091	0.084	0.098	0.111	0.097	0.013	0.096	0.014
15	0.012	0.086	0.090	0.094	0.095	0.075	0.014	0.088	0.013
16	0.011	0.085	0.074	0.079	0.072	0.059	0.013	0.074	0.012
17	0.013	0.050	0.037	0.041	0.036	0.032	0.012	0.039	0.012
18	0.010	0.020	0.023	0.019	0.019	0.015	0.012	0.019	0.011
19	0.009	0.010	0.020	0.014	0.019	0.011	0.008	0.015	0.009
20	0.008	0.010	0.018	0.011	0.019	0.010	0.009	0.013	0.008
21	0.006	0.010	0.016	0.010	0.013	0.005	0.007	0.011	0.006
22	0.007	0.007	0.009	0.008	0.009	0.004	0.007	0.008	0.007
23	0.004	0.007	0.006	0.007	0.006	0.003	0.004	0.006	0.004
Annual kWh	115	923	882	907	919	831	113	4,691	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 27	115	923	882	907	919	831	113	4,691
Error	78.5%	53.0%	55.9%	54.6%	53.9%	55.3%	83.9%	57.56%

SIMULATION RESULTS: Parameter Set 28									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.003	0.002	0.005	0.004	0.004	0.003	0.002	0.003	0.002
1	0.002	0.003	0.004	0.003	0.004	0.003	0.002	0.003	0.002
2	0.002	0.003	0.005	0.005	0.003	0.002	0.002	0.004	0.002
3	0.001	0.003	0.005	0.005	0.004	0.002	0.001	0.004	0.001
4	0.002	0.003	0.004	0.006	0.003	0.002	0.002	0.004	0.002
5	0.003	0.005	0.006	0.008	0.007	0.003	0.002	0.006	0.003
6	0.003	0.052	0.046	0.048	0.046	0.049	0.003	0.048	0.003
7	0.004	0.142	0.129	0.136	0.133	0.140	0.003	0.136	0.004
8	0.006	0.157	0.141	0.143	0.146	0.136	0.006	0.145	0.006
9	0.007	0.153	0.139	0.141	0.144	0.138	0.010	0.143	0.008
10	0.008	0.147	0.126	0.124	0.125	0.126	0.010	0.130	0.009
11	0.006	0.084	0.073	0.071	0.065	0.076	0.011	0.074	0.008
12	0.009	0.080	0.073	0.065	0.065	0.071	0.008	0.071	0.009
13	0.012	0.102	0.099	0.090	0.096	0.094	0.011	0.096	0.011
14	0.014	0.079	0.079	0.080	0.085	0.079	0.013	0.080	0.013
15	0.014	0.077	0.079	0.085	0.082	0.066	0.013	0.078	0.013
16	0.013	0.081	0.070	0.073	0.072	0.060	0.013	0.071	0.013
17	0.014	0.048	0.035	0.035	0.035	0.035	0.012	0.038	0.013
18	0.009	0.017	0.020	0.018	0.018	0.024	0.009	0.019	0.009
19	0.006	0.011	0.014	0.009	0.013	0.011	0.007	0.011	0.007
20	0.006	0.007	0.011	0.010	0.011	0.007	0.009	0.009	0.007
21	0.004	0.006	0.008	0.009	0.011	0.008	0.010	0.008	0.007
22	0.004	0.006	0.007	0.006	0.008	0.005	0.011	0.007	0.007
23	0.003	0.006	0.005	0.006	0.004	0.002	0.005	0.005	0.004
Annual kWh	102	853	792	791	807	765	116	4,227	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 28	102	853	792	791	807	765	116	4,227
Error	80.9%	56.6%	60.4%	60.4%	59.5%	58.8%	83.5%	61.76%

SIMULATION SETTINGS: Parameter Set 29

On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.76, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 29

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.003	0.003	0.005	0.004	0.005	0.003	0.003	0.004	0.003
1	0.003	0.002	0.005	0.004	0.004	0.002	0.003	0.003	0.003
2	0.004	0.003	0.004	0.006	0.004	0.003	0.003	0.004	0.003
3	0.004	0.005	0.004	0.004	0.005	0.003	0.003	0.004	0.003
4	0.003	0.005	0.004	0.004	0.004	0.002	0.002	0.004	0.003
5	0.003	0.007	0.005	0.008	0.007	0.004	0.002	0.006	0.003
6	0.003	0.047	0.044	0.047	0.042	0.045	0.003	0.045	0.003
7	0.004	0.141	0.124	0.141	0.129	0.132	0.004	0.133	0.004
8	0.006	0.149	0.135	0.150	0.152	0.130	0.007	0.143	0.007
9	0.008	0.149	0.141	0.145	0.147	0.135	0.008	0.143	0.008
10	0.011	0.137	0.125	0.134	0.130	0.119	0.010	0.129	0.011
11	0.009	0.070	0.071	0.068	0.066	0.071	0.013	0.069	0.011
12	0.011	0.079	0.067	0.074	0.064	0.077	0.013	0.072	0.012
13	0.015	0.095	0.093	0.095	0.096	0.095	0.013	0.095	0.014
14	0.016	0.077	0.082	0.084	0.090	0.077	0.015	0.082	0.016
15	0.013	0.086	0.087	0.090	0.083	0.066	0.016	0.082	0.015
16	0.013	0.076	0.076	0.069	0.067	0.057	0.018	0.069	0.015
17	0.013	0.039	0.038	0.041	0.034	0.038	0.016	0.038	0.015
18	0.008	0.017	0.021	0.022	0.021	0.021	0.014	0.020	0.011
19	0.004	0.010	0.013	0.014	0.018	0.007	0.011	0.012	0.008
20	0.006	0.010	0.011	0.011	0.024	0.006	0.008	0.012	0.007
21	0.005	0.007	0.011	0.012	0.021	0.005	0.008	0.011	0.007
22	0.006	0.007	0.011	0.008	0.012	0.003	0.007	0.008	0.006
23	0.004	0.007	0.006	0.007	0.006	0.003	0.004	0.006	0.004
Annual kWh	118	821	793	832	841	738	135	4,277	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 29	118	821	793	832	841	738	135	4,277
Error	78.0%	58.2%	60.3%	58.4%	57.8%	60.3%	80.8%	61.30%

SIMULATION SETTINGS: Parameter Set 30

On DC	50% = 0.77, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.76, 50% = 0
Int Off DC	50% = 0.81, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 30

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.002	0.003	0.005	0.003	0.007	0.005	0.002	0.004	0.002
1	0.003	0.003	0.002	0.003	0.006	0.004	0.002	0.004	0.003
2	0.003	0.003	0.003	0.004	0.006	0.005	0.001	0.004	0.002
3	0.003	0.004	0.003	0.004	0.005	0.007	0.001	0.005	0.002
4	0.002	0.003	0.004	0.004	0.004	0.006	0.001	0.004	0.001
5	0.001	0.009	0.008	0.008	0.009	0.010	0.001	0.009	0.001
6	0.002	0.069	0.069	0.064	0.068	0.059	0.002	0.066	0.002
7	0.003	0.176	0.174	0.165	0.168	0.163	0.003	0.169	0.003
8	0.006	0.188	0.175	0.176	0.180	0.166	0.006	0.177	0.006
9	0.006	0.185	0.170	0.168	0.171	0.167	0.007	0.172	0.007
10	0.012	0.179	0.159	0.153	0.162	0.164	0.011	0.163	0.012
11	0.010	0.097	0.092	0.087	0.081	0.091	0.013	0.090	0.012
12	0.015	0.101	0.089	0.084	0.078	0.092	0.012	0.089	0.013
13	0.018	0.133	0.111	0.121	0.119	0.130	0.011	0.123	0.015
14	0.019	0.098	0.104	0.104	0.113	0.110	0.013	0.106	0.016
15	0.019	0.103	0.104	0.114	0.100	0.085	0.015	0.101	0.017
16	0.017	0.096	0.084	0.089	0.086	0.071	0.014	0.085	0.016
17	0.015	0.054	0.042	0.045	0.043	0.040	0.011	0.045	0.013
18	0.012	0.017	0.021	0.019	0.020	0.021	0.010	0.020	0.011
19	0.008	0.010	0.015	0.012	0.018	0.011	0.008	0.013	0.008
20	0.008	0.010	0.011	0.010	0.022	0.007	0.006	0.012	0.007
21	0.006	0.008	0.010	0.011	0.017	0.006	0.005	0.010	0.006
22	0.006	0.005	0.007	0.008	0.012	0.004	0.005	0.007	0.005
23	0.004	0.005	0.004	0.008	0.006	0.003	0.003	0.005	0.004
Annual kWh	133	1,044	983	981	1,024	953	110	5,230	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 30	133	1,044	983	981	1,024	953	110	5,230
Error	75.1%	46.9%	50.8%	50.9%	48.6%	48.7%	84.3%	52.68%

		SIMULATION SETTINGS: Parameter Set 31
On DC	50% = 0.98, 8% = 1, 42% = 0	
Off DC	8% = 0.5, 92% = 0	
Int On DC	50% = 0.92, 8% = 1, 42% = 0	
Int Off DC	50% = 0.99, 8% = 1, 42% = 0	
R or L	All = 1	
mu	0.9	

				SIMULATION RESULTS: Parameter Set 31					
	1	**2**	**3**	**4**	**5**	**6**	**7**		
Hour	**Sun**	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Weekday**	**Weekend Day**
0	0.005	0.005	0.004	0.005	0.006	0.003	0.004	0.005	0.004
1	0.005	0.005	0.002	0.003	0.004	0.004	0.003	0.004	0.004
2	0.005	0.005	0.004	0.004	0.005	0.004	0.003	0.004	0.004
3	0.004	0.004	0.003	0.003	0.004	0.004	0.004	0.004	0.004
4	0.004	0.005	0.003	0.004	0.003	0.005	0.003	0.004	0.004
5	0.005	0.006	0.006	0.007	0.006	0.006	0.003	0.006	0.004
6	0.005	0.064	0.061	0.060	0.058	0.058	0.004	0.060	0.004
7	0.006	0.197	0.189	0.190	0.185	0.182	0.004	0.189	0.005
8	0.009	0.273	0.275	0.270	0.258	0.239	0.010	0.263	0.010
9	0.014	0.320	0.307	0.303	0.292	0.273	0.013	0.299	0.014
10	0.024	0.353	0.333	0.336	0.320	0.297	0.025	0.328	0.024
11	0.020	0.266	0.258	0.259	0.246	0.231	0.027	0.252	0.023
12	0.033	0.270	0.253	0.248	0.230	0.223	0.027	0.245	0.030
13	0.038	0.324	0.309	0.310	0.298	0.302	0.030	0.308	0.034
14	0.040	0.311	0.318	0.321	0.330	0.307	0.035	0.317	0.038
15	0.034	0.292	0.304	0.299	0.304	0.279	0.040	0.296	0.037
16	0.034	0.274	0.275	0.267	0.272	0.249	0.045	0.267	0.040
17	0.029	0.187	0.181	0.177	0.166	0.160	0.034	0.174	0.032
18	0.021	0.079	0.089	0.080	0.079	0.076	0.024	0.081	0.023
19	0.011	0.038	0.043	0.037	0.040	0.028	0.018	0.037	0.015
20	0.009	0.020	0.025	0.024	0.031	0.017	0.016	0.023	0.012
21	0.008	0.012	0.018	0.017	0.024	0.011	0.014	0.016	0.011
22	0.008	0.010	0.013	0.011	0.016	0.005	0.010	0.011	0.009
23	0.005	0.006	0.008	0.008	0.008	0.005	0.007	0.007	0.006
Annual kWh	252	2,229	2,198	2,172	2,173	1,988	270	11,282	

	Sun	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Total Annual**
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 31	252	2,229	2,198	2,172	2,173	1,988	270	11,282
Error	53.0%	13.4%	10.0%	8.7%	9.0%	7.0%	61.6%	2.08%

SIMULATION SETTINGS: Parameter Set 32	
On DC	50% = 0.98, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.92, 50% = 0
Int Off DC	50% = 0.99, 50% = 0
R or L	All = 1
mu	0.9

SIMULATION RESULTS: Parameter Set 32

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.005	0.005	0.006	0.005	0.004	0.003	0.004	0.004	0.004
1	0.004	0.005	0.004	0.004	0.003	0.004	0.003	0.004	0.004
2	0.005	0.006	0.004	0.004	0.004	0.003	0.003	0.004	0.004
3	0.005	0.004	0.004	0.004	0.003	0.003	0.003	0.003	0.004
4	0.005	0.004	0.003	0.004	0.004	0.003	0.004	0.004	0.004
5	0.004	0.007	0.007	0.008	0.007	0.006	0.004	0.007	0.004
6	0.005	0.067	0.069	0.066	0.063	0.065	0.005	0.066	0.005
7	0.008	0.190	0.185	0.193	0.183	0.187	0.005	0.188	0.006
8	0.012	0.240	0.229	0.235	0.230	0.214	0.011	0.229	0.011
9	0.016	0.259	0.246	0.257	0.242	0.238	0.016	0.249	0.016
10	0.028	0.286	0.273	0.267	0.262	0.265	0.021	0.271	0.025
11	0.022	0.235	0.226	0.220	0.210	0.215	0.025	0.221	0.024
12	0.036	0.240	0.227	0.226	0.207	0.209	0.026	0.222	0.031
13	0.042	0.282	0.263	0.263	0.259	0.258	0.028	0.265	0.035
14	0.042	0.246	0.255	0.252	0.263	0.248	0.031	0.253	0.036
15	0.035	0.235	0.245	0.250	0.250	0.229	0.034	0.242	0.035
16	0.031	0.229	0.229	0.220	0.228	0.195	0.041	0.220	0.036
17	0.027	0.143	0.140	0.130	0.128	0.120	0.032	0.132	0.030
18	0.019	0.051	0.063	0.048	0.052	0.054	0.022	0.054	0.021
19	0.014	0.025	0.031	0.025	0.031	0.021	0.018	0.027	0.016
20	0.009	0.015	0.020	0.019	0.023	0.013	0.015	0.018	0.012
21	0.007	0.010	0.015	0.014	0.017	0.007	0.017	0.013	0.012
22	0.006	0.008	0.014	0.009	0.012	0.005	0.013	0.010	0.009
23	0.005	0.008	0.007	0.008	0.008	0.005	0.010	0.007	0.007
Annual kWh	263	1,875	1,850	1,827	1,838	1,722	262	9,638	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 32	263	1,875	1,850	1,827	1,838	1,722	262	9,638
Error	50.9%	4.6%	7.4%	8.6%	7.8%	7.4%	62.7%	12.79%

SIMULATION SETTINGS: Parameter Set 33

On DC	50% = 0.77, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.72, 50% = 0
Int Off DC	50% = 0.79, 50% = 0
R or L	All = 1
mu	0.04

SIMULATION RESULTS: Parameter Set 33

	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.005	0.003	0.004	0.004	0.006	0.005	0.003	0.005	0.004
1	0.004	0.004	0.003	0.003	0.005	0.004	0.003	0.004	0.004
2	0.003	0.005	0.004	0.004	0.005	0.005	0.003	0.004	0.003
3	0.003	0.004	0.003	0.004	0.005	0.005	0.002	0.004	0.003
4	0.003	0.004	0.003	0.004	0.004	0.004	0.003	0.004	0.003
5	0.003	0.007	0.006	0.007	0.007	0.005	0.004	0.006	0.003
6	0.004	0.050	0.048	0.048	0.049	0.045	0.004	0.048	0.004
7	0.006	0.152	0.149	0.153	0.147	0.146	0.006	0.149	0.006
8	0.008	0.183	0.175	0.177	0.175	0.160	0.010	0.174	0.009
9	0.010	0.179	0.174	0.173	0.175	0.166	0.016	0.173	0.013
10	0.017	0.174	0.152	0.154	0.158	0.148	0.022	0.157	0.019
11	0.013	0.101	0.088	0.079	0.083	0.088	0.022	0.088	0.018
12	0.018	0.096	0.090	0.075	0.071	0.080	0.016	0.082	0.017
13	0.022	0.115	0.105	0.103	0.116	0.111	0.018	0.110	0.020
14	0.021	0.092	0.094	0.086	0.111	0.102	0.021	0.097	0.021
15	0.018	0.096	0.095	0.097	0.094	0.087	0.020	0.094	0.019
16	0.018	0.090	0.085	0.081	0.084	0.079	0.024	0.084	0.021
17	0.017	0.050	0.047	0.045	0.045	0.047	0.017	0.047	0.017
18	0.014	0.019	0.027	0.020	0.020	0.025	0.012	0.022	0.013
19	0.010	0.013	0.021	0.013	0.019	0.011	0.012	0.015	0.011
20	0.009	0.012	0.014	0.011	0.019	0.010	0.015	0.013	0.012
21	0.006	0.008	0.013	0.013	0.016	0.007	0.015	0.012	0.010
22	0.007	0.007	0.013	0.008	0.012	0.004	0.011	0.009	0.009
23	0.004	0.006	0.008	0.008	0.008	0.004	0.007	0.007	0.006
Annual kWh	161	985	951	918	979	902	191	5,087	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
Sim 33	161	985	951	918	979	902	191	5,087
Error	69.9%	49.9%	52.4%	54.0%	50.9%	51.5%	72.8%	53.98%

APPENDIX F: REVISED VALIDATION STUDY RESULTS

SIMULATION SETTINGS: Parameter Set M1	
On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.76, 50% = 0
R or L	All = 1
mu	0.04
alpha	-1
lambda	4
delta	0.7
nu	3

SIMULATION RESULTS: Parameter Set M1									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.004	0.003	0.006	0.004	0.006	0.003	0.004	0.004	0.004
1	0.004	0.003	0.003	0.003	0.005	0.002	0.003	0.003	0.003
2	0.004	0.003	0.003	0.004	0.006	0.004	0.002	0.004	0.003
3	0.005	0.004	0.003	0.004	0.005	0.004	0.002	0.004	0.003
4	0.004	0.004	0.003	0.004	0.004	0.003	0.002	0.004	0.003
5	0.005	0.007	0.007	0.008	0.008	0.006	0.002	0.007	0.004
6	0.004	0.058	0.050	0.053	0.051	0.052	0.003	0.053	0.004
7	0.005	0.165	0.149	0.158	0.157	0.148	0.004	0.155	0.005
8	0.007	0.168	0.165	0.155	0.175	0.151	0.008	0.163	0.008
9	0.011	0.164	0.162	0.155	0.169	0.153	0.010	0.161	0.011
10	0.016	0.149	0.152	0.145	0.149	0.141	0.011	0.147	0.014
11	0.012	0.082	0.077	0.073	0.081	0.077	0.014	0.078	0.013
12	0.024	0.095	0.080	0.077	0.069	0.074	0.011	0.079	0.018
13	0.020	0.122	0.108	0.104	0.098	0.099	0.014	0.106	0.017
14	0.022	0.090	0.094	0.084	0.095	0.081	0.017	0.089	0.019
15	0.018	0.090	0.087	0.086	0.085	0.071	0.016	0.084	0.017
16	0.016	0.082	0.072	0.074	0.072	0.066	0.020	0.073	0.018
17	0.016	0.046	0.043	0.047	0.038	0.034	0.017	0.042	0.016
18	0.010	0.017	0.026	0.022	0.019	0.024	0.014	0.022	0.012
19	0.008	0.012	0.018	0.012	0.021	0.011	0.015	0.015	0.011
20	0.008	0.013	0.013	0.011	0.020	0.012	0.013	0.014	0.010
21	0.006	0.009	0.014	0.012	0.015	0.006	0.013	0.011	0.009
22	0.006	0.008	0.013	0.009	0.009	0.005	0.009	0.009	0.007
23	0.005	0.007	0.007	0.007	0.006	0.005	0.006	0.007	0.006
Annual kWh	162	937	906	878	913	825	153	4,774	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
M1	278	1,715	1,590	1,692	1,745	1,665	249	8,935
Error	48.3%	12.7%	20.4%	15.3%	12.4%	10.4%	64.5%	19.16%

SIMULATION SETTINGS: Parameter Set M2	
On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.76, 50% = 0
R or L	All = 1
mu	0.04
alpha	-1
lambda	5
delta	1
nu	10

SIMULATION RESULTS: Parameter Set M2									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.014	0.009	0.035	0.032	0.031	0.024	0.011	0.026	0.013
1	0.012	0.013	0.025	0.028	0.025	0.018	0.008	0.022	0.010
2	0.010	0.021	0.024	0.029	0.022	0.018	0.006	0.023	0.008
3	0.010	0.018	0.025	0.026	0.019	0.019	0.005	0.022	0.008
4	0.008	0.024	0.026	0.031	0.026	0.021	0.008	0.026	0.008
5	0.002	0.038	0.044	0.041	0.036	0.039	0.002	0.039	0.002
6	0.003	0.118	0.130	0.115	0.109	0.122	0.003	0.119	0.003
7	0.005	0.191	0.176	0.171	0.178	0.183	0.004	0.180	0.004
8	0.006	0.170	0.149	0.153	0.165	0.148	0.006	0.157	0.006
9	0.006	0.163	0.140	0.143	0.153	0.149	0.007	0.150	0.006
10	0.008	0.142	0.125	0.121	0.124	0.125	0.010	0.127	0.009
11	0.009	0.114	0.101	0.103	0.101	0.101	0.008	0.104	0.008
12	0.008	0.068	0.067	0.067	0.065	0.064	0.008	0.066	0.008
13	0.009	0.073	0.066	0.072	0.053	0.059	0.006	0.064	0.008
14	0.011	0.087	0.081	0.086	0.086	0.084	0.009	0.085	0.010
15	0.014	0.093	0.086	0.112	0.112	0.096	0.010	0.100	0.012
16	0.014	0.079	0.077	0.084	0.099	0.087	0.010	0.085	0.012
17	0.013	0.097	0.110	0.125	0.114	0.092	0.013	0.108	0.013
18	0.015	0.104	0.108	0.099	0.107	0.088	0.014	0.101	0.014
19	0.013	0.093	0.091	0.086	0.082	0.079	0.014	0.086	0.014
20	0.013	0.062	0.055	0.053	0.049	0.055	0.016	0.055	0.014
21	0.010	0.031	0.031	0.029	0.026	0.032	0.012	0.030	0.011
22	0.008	0.019	0.021	0.015	0.019	0.013	0.009	0.017	0.008
23	0.007	0.025	0.026	0.019	0.021	0.012	0.011	0.021	0.009
Annual kWh	153	1,239	1,218	1,232	1,220	1,157	141	6,362	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
M2	153	1,239	1,218	1,232	1,220	1,157	141	6,362
Error	71.5%	37.0%	39.0%	38.3%	38.8%	37.7%	79.9%	42.44%

SIMULATION SETTINGS: Parameter Set M3	
On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.76, 50% = 0
R or L	All = 1
mu	0.04
alpha	0
lambda	5
delta	1
nu	20

SIMULATION RESULTS: Parameter Set M3									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.033	0.038	0.065	0.039	0.067	0.040	0.025	0.050	0.029
1	0.026	0.040	0.038	0.027	0.048	0.030	0.024	0.037	0.025
2	0.026	0.043	0.042	0.029	0.045	0.030	0.021	0.038	0.024
3	0.025	0.051	0.042	0.026	0.041	0.034	0.016	0.039	0.021
4	0.022	0.048	0.036	0.026	0.042	0.034	0.016	0.037	0.019
5	0.017	0.063	0.052	0.053	0.057	0.047	0.016	0.054	0.017
6	0.001	0.040	0.039	0.045	0.043	0.042	0.003	0.042	0.002
7	0.003	0.120	0.108	0.117	0.115	0.111	0.005	0.114	0.004
8	0.005	0.173	0.143	0.148	0.161	0.150	0.007	0.155	0.006
9	0.007	0.144	0.120	0.124	0.129	0.121	0.006	0.128	0.006
10	0.007	0.155	0.136	0.134	0.135	0.128	0.009	0.137	0.008
11	0.013	0.130	0.114	0.114	0.108	0.103	0.010	0.114	0.011
12	0.012	0.107	0.092	0.103	0.089	0.086	0.010	0.095	0.011
13	0.010	0.068	0.060	0.065	0.055	0.054	0.012	0.060	0.011
14	0.013	0.073	0.060	0.060	0.051	0.056	0.013	0.060	0.013
15	0.016	0.091	0.086	0.079	0.082	0.091	0.014	0.086	0.015
16	0.017	0.101	0.096	0.099	0.111	0.107	0.016	0.103	0.017
17	0.018	0.090	0.095	0.093	0.107	0.104	0.017	0.098	0.018
18	0.019	0.113	0.118	0.127	0.119	0.114	0.019	0.118	0.019
19	0.019	0.116	0.114	0.111	0.114	0.111	0.022	0.113	0.020
20	0.020	0.114	0.108	0.101	0.098	0.108	0.024	0.106	0.022
21	0.019	0.076	0.074	0.068	0.064	0.076	0.024	0.072	0.022
22	0.014	0.034	0.042	0.035	0.032	0.043	0.018	0.037	0.016
23	0.009	0.038	0.037	0.040	0.035	0.022	0.022	0.034	0.015
Annual kWh	249	1,384	1,282	1,247	1,303	1,232	247	6,944	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
M3	249	1,384	1,282	1,247	1,303	1,232	247	6,944
Error	53.7%	29.6%	35.8%	37.6%	34.6%	33.7%	64.8%	37.17%

SIMULATION SETTINGS: Parameter Set M4	
On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.9, 50% = 0
R or L	All = 1
mu	0.04
alpha	0
lambda	5
delta	1
nu	20

SIMULATION RESULTS: Parameter Set M4									
	1	2	3	4	5	6	7		
Hour	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Weekday	Weekend Day
0	0.042	0.039	0.080	0.054	0.077	0.061	0.039	0.062	0.041
1	0.039	0.045	0.050	0.037	0.055	0.045	0.039	0.046	0.039
2	0.038	0.055	0.052	0.041	0.049	0.046	0.036	0.049	0.037
3	0.036	0.056	0.051	0.039	0.043	0.050	0.027	0.048	0.032
4	0.033	0.051	0.047	0.038	0.041	0.047	0.027	0.045	0.030
5	0.025	0.049	0.048	0.052	0.038	0.048	0.022	0.047	0.024
6	0.002	0.025	0.023	0.024	0.022	0.024	0.003	0.024	0.003
7	0.004	0.105	0.103	0.097	0.097	0.101	0.005	0.100	0.004
8	0.005	0.175	0.170	0.163	0.164	0.158	0.006	0.166	0.005
9	0.009	0.179	0.176	0.171	0.170	0.151	0.009	0.169	0.009
10	0.009	0.192	0.185	0.183	0.182	0.168	0.011	0.182	0.010
11	0.014	0.176	0.167	0.167	0.166	0.155	0.015	0.166	0.015
12	0.014	0.157	0.152	0.157	0.148	0.144	0.015	0.152	0.014
13	0.013	0.111	0.110	0.105	0.098	0.098	0.019	0.104	0.016
14	0.019	0.107	0.100	0.091	0.077	0.088	0.016	0.093	0.018
15	0.023	0.133	0.125	0.119	0.112	0.123	0.018	0.122	0.020
16	0.024	0.149	0.140	0.150	0.151	0.141	0.017	0.146	0.021
17	0.026	0.142	0.134	0.144	0.160	0.139	0.022	0.144	0.024
18	0.026	0.157	0.156	0.159	0.161	0.142	0.026	0.155	0.026
19	0.024	0.153	0.155	0.153	0.157	0.140	0.030	0.152	0.027
20	0.025	0.148	0.151	0.138	0.144	0.128	0.033	0.142	0.029
21	0.024	0.105	0.108	0.098	0.097	0.092	0.030	0.100	0.027
22	0.019	0.052	0.065	0.055	0.055	0.055	0.022	0.056	0.021
23	0.011	0.051	0.053	0.055	0.051	0.032	0.027	0.048	0.019
Annual kWh	338	1,749	1,742	1,666	1,685	1,591	344	9,116	

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
M4	338	1,749	1,742	1,666	1,685	1,591	344	9,116
Error	36.9%	11.0%	12.8%	16.6%	15.5%	14.4%	51.0%	17.52%

SIMULATION SETTINGS: Parameter Set M5	
On DC	50% = 0.64, 50% = 0
Off DC	All = 0
Int On DC	50% = 0.68, 50% = 0
Int Off DC	50% = 0.9, 50% = 0
R or L	All = 1
mu	0.04
alpha	0
lambda	6
delta	1
nu	20

SIMULATION RESULTS: Parameter Set M5									
	1	**2**	**3**	**4**	**5**	**6**	**7**		
Hour	**Sun**	**Mon**	**Tue**	**Wed**	**Thu**	**Fri**	**Sat**	**Weekday**	**Weekend Day**
0	0.029	0.030	0.046	0.051	0.081	0.049	0.021	0.051	0.025
1	0.026	0.039	0.028	0.039	0.064	0.041	0.019	0.042	0.022
2	0.024	0.049	0.029	0.039	0.061	0.041	0.019	0.044	0.022
3	0.027	0.044	0.029	0.038	0.060	0.044	0.015	0.043	0.021
4	0.024	0.049	0.023	0.035	0.060	0.042	0.017	0.042	0.021
5	0.017	0.061	0.036	0.050	0.057	0.046	0.015	0.050	0.016
6	0.002	0.035	0.033	0.033	0.032	0.036	0.003	0.034	0.003
7	0.002	0.106	0.101	0.102	0.094	0.102	0.004	0.101	0.003
8	0.003	0.173	0.157	0.158	0.152	0.161	0.005	0.160	0.004
9	0.006	0.178	0.164	0.166	0.170	0.174	0.009	0.170	0.008
10	0.008	0.175	0.150	0.158	0.151	0.158	0.009	0.158	0.008
11	0.011	0.166	0.151	0.151	0.149	0.141	0.009	0.152	0.010
12	0.015	0.177	0.149	0.163	0.161	0.154	0.011	0.161	0.013
13	0.012	0.122	0.111	0.120	0.108	0.111	0.013	0.114	0.012
14	0.014	0.097	0.089	0.106	0.084	0.086	0.013	0.092	0.013
15	0.017	0.117	0.106	0.112	0.091	0.105	0.016	0.106	0.016
16	0.019	0.140	0.122	0.142	0.126	0.146	0.016	0.135	0.017
17	0.021	0.145	0.141	0.156	0.165	0.159	0.017	0.153	0.019
18	0.024	0.122	0.138	0.141	0.153	0.152	0.020	0.141	0.022
19	0.023	0.137	0.151	0.157	0.161	0.150	0.023	0.151	0.023
20	0.026	0.149	0.152	0.146	0.166	0.149	0.027	0.152	0.026
21	0.026	0.128	0.128	0.128	0.130	0.123	0.026	0.127	0.026
22	0.023	0.080	0.085	0.078	0.079	0.077	0.022	0.080	0.022
23	0.014	0.044	0.056	0.058	0.052	0.042	0.024	0.050	0.019
Annual kWh	278	1,715	1,590	1,692	1,745	1,665	249	8,935	

278

	Sun	Mon	Tue	Wed	Thu	Fri	Sat	Total Annual
Data	537	1,965	1,998	1,998	1,993	1,859	702	11,052
M5	278	1,715	1,590	1,692	1,745	1,665	249	8,935
Error	48.3%	12.7%	20.4%	15.3%	12.4%	10.4%	64.5%	19.16%

APPENDIX G: DETERMINISTIC SCHEDULE ANALYSIS RESULTS

LPD	0.87									
	AS1	AS2	AS3	AS4	AS5	AS6	ACM	DOE-2	Hours	Data
Annual Energy, [kWh]	15,148	2,492	3,646	8,666	3,372	8,789	40,514	37,965	30,350	33,716
Peak Demand, [kW]	9.57	3.05	3.31	5.66	3.57	6.79	10.94	11.59	12.92	6.83

LPD	1.1								
	AS1	AS2	AS3	AS4	AS5	AS6	ACM	DOE-2	Hours
Annual Energy, [kWh]	19,153	3,151	4,611	10,957	4,263	11,112	51,224	48,002	38,242
Peak Demand, [kW]	12.10	3.85	4.18	7.15	4.51	8.58	13.84	14.65	16.28

WEEKDAY Relative Intensity Profiles										
Hour of Day	AS1	AS2	AS3	AS4	AS5	AS6	ACM	ACM	Building Hours	Submetered
0	0.6%	0.2%	0.2%	0.4%	0.2%	0.4%	10.0%	5.0%	5.0%	22.8%
1	0.5%	0.3%	0.2%	0.4%	0.2%	0.4%	5.0%	5.0%	5.0%	17.4%
2	0.6%	0.2%	0.3%	0.4%	0.2%	0.4%	5.0%	5.0%	5.0%	15.4%
3	0.5%	0.2%	0.2%	0.4%	0.3%	0.5%	5.0%	5.0%	5.0%	14.7%
4	0.6%	0.3%	0.2%	0.4%	0.2%	0.5%	5.0%	5.0%	5.0%	14.5%
5	0.8%	0.5%	0.5%	0.7%	0.5%	1.0%	10.0%	5.0%	5.0%	14.9%
6	5.4%	3.3%	3.8%	5.9%	3.8%	8.1%	20.0%	10.0%	5.0%	19.2%
7	22.7%	8.9%	10.0%	17.5%	10.3%	24.2%	40.0%	10.0%	5.0%	34.9%
8	34.3%	7.9%	11.5%	21.7%	10.9%	28.1%	70.0%	30.0%	5.0%	46.9%
9	39.7%	7.5%	11.2%	24.0%	10.3%	27.3%	80.0%	90.0%	100.0%	50.6%
10	45.2%	6.6%	10.3%	26.0%	9.3%	27.4%	85.0%	90.0%	100.0%	50.0%
11	35.9%	3.5%	6.5%	19.1%	5.0%	17.8%	85.0%	90.0%	100.0%	50.5%
12	32.3%	4.1%	7.0%	17.9%	5.8%	16.3%	85.0%	90.0%	100.0%	47.8%
13	41.5%	5.3%	9.0%	22.8%	7.8%	20.9%	85.0%	90.0%	100.0%	48.5%
14	42.9%	4.1%	7.7%	22.3%	6.5%	19.3%	85.0%	90.0%	100.0%	49.4%
15	40.7%	4.5%	7.2%	21.5%	6.4%	18.5%	85.0%	90.0%	100.0%	49.7%
16	36.4%	4.3%	6.9%	19.3%	6.1%	15.7%	85.0%	90.0%	100.0%	50.0%
17	23.1%	2.7%	4.0%	11.6%	3.9%	8.5%	85.0%	90.0%	100.0%	47.1%
18	11.1%	1.5%	2.0%	5.3%	2.1%	3.8%	80.0%	50.0%	5.0%	44.0%
19	5.6%	1.0%	1.2%	2.7%	1.6%	2.4%	35.0%	30.0%	5.0%	41.5%
20	3.8%	0.9%	1.0%	1.9%	1.3%	1.9%	10.0%	30.0%	5.0%	44.9%
21	2.6%	0.7%	0.8%	1.4%	0.9%	1.5%	10.0%	20.0%	5.0%	43.0%
22	1.6%	0.5%	0.6%	1.0%	0.6%	1.1%	10.0%	20.0%	5.0%	37.1%
23	1.0%	0.4%	0.4%	0.6%	0.4%	0.8%	10.0%	10.0%	5.0%	33.0%

Saturday Relative Intensity Use Profiles									
Hour of Day	AS1	AS2	AS3	AS4	AS5	AS6	ACM	ACM	Building Hours	Submetered
0	0.3%	0.1%	0.2%	0.3%	0.2%	0.5%	10.0%	5.0%	0.0%	26.6%
1	0.3%	0.1%	0.1%	0.2%	0.1%	0.5%	5.0%	5.0%	0.0%	19.7%
2	0.3%	0.2%	0.2%	0.2%	0.1%	0.4%	5.0%	5.0%	0.0%	16.9%
3	0.3%	0.2%	0.2%	0.2%	0.1%	0.4%	5.0%	5.0%	0.0%	16.8%
4	0.3%	0.2%	0.2%	0.2%	0.1%	0.4%	5.0%	5.0%	0.0%	16.5%
5	0.3%	0.1%	0.3%	0.2%	0.1%	0.4%	5.0%	5.0%	0.0%	15.8%
6	0.3%	0.2%	0.2%	0.3%	0.3%	0.6%	10.0%	5.0%	0.0%	12.5%
7	0.6%	0.3%	0.3%	0.3%	0.2%	0.5%	15.0%	10.0%	0.0%	9.7%
8	1.3%	0.4%	0.5%	0.8%	0.4%	1.6%	25.0%	10.0%	0.0%	7.8%
9	1.9%	0.5%	0.7%	1.0%	0.6%	1.6%	25.0%	30.0%	0.0%	10.7%
10	2.5%	0.7%	0.8%	1.5%	0.7%	1.8%	25.0%	30.0%	0.0%	11.4%
11	3.2%	0.9%	0.8%	2.0%	1.0%	2.3%	25.0%	30.0%	0.0%	11.3%
12	4.0%	0.6%	0.9%	2.1%	1.0%	2.4%	25.0%	30.0%	0.0%	11.8%
13	4.0%	0.7%	1.0%	2.2%	0.9%	2.6%	25.0%	15.0%	0.0%	10.8%
14	4.7%	0.8%	1.1%	2.7%	0.9%	3.3%	25.0%	15.0%	0.0%	10.3%
15	5.9%	0.8%	1.2%	3.4%	1.3%	3.1%	20.0%	15.0%	0.0%	9.1%
16	6.5%	1.0%	1.3%	3.6%	1.1%	3.6%	20.0%	15.0%	0.0%	10.0%
17	5.6%	0.9%	1.0%	3.0%	1.3%	2.8%	20.0%	15.0%	0.0%	10.6%
18	4.3%	0.8%	0.7%	2.1%	0.9%	2.3%	15.0%	5.0%	0.0%	11.6%
19	2.8%	0.7%	0.5%	1.6%	0.6%	1.6%	10.0%	5.0%	0.0%	12.2%
20	2.0%	0.7%	0.7%	1.5%	0.6%	1.7%	10.0%	5.0%	0.0%	14.7%
21	1.8%	0.5%	0.6%	1.0%	0.7%	1.7%	10.0%	5.0%	0.0%	16.8%
22	1.4%	0.4%	0.4%	0.7%	0.5%	1.1%	10.0%	5.0%	0.0%	15.3%
23	0.8%	0.3%	0.3%	0.4%	0.5%	1.0%	10.0%	5.0%	0.0%	14.5%

Sunday Relative Intensity Use Profiles										
Hour of Day	AS1	AS2	AS3	AS4	AS5	AS6	ACM	ACM	Building Hours	Submetered
0	0.4%	0.2%	0.2%	0.4%	0.2%	0.6%	5.0%	5.0%	0.0%	14.4%
1	0.4%	0.2%	0.2%	0.3%	0.2%	0.6%	5.0%	5.0%	0.0%	14.4%
2	0.4%	0.1%	0.1%	0.3%	0.1%	0.6%	5.0%	5.0%	0.0%	14.2%
3	0.4%	0.2%	0.2%	0.3%	0.2%	0.4%	5.0%	5.0%	0.0%	13.8%
4	0.4%	0.1%	0.2%	0.4%	0.2%	0.5%	5.0%	5.0%	0.0%	13.7%
5	0.5%	0.2%	0.2%	0.5%	0.2%	0.5%	5.0%	5.0%	0.0%	13.1%
6	0.5%	0.2%	0.2%	0.4%	0.1%	0.5%	10.0%	5.0%	0.0%	10.4%
7	0.9%	0.3%	0.3%	0.6%	0.2%	0.8%	10.0%	5.0%	0.0%	7.1%
8	1.2%	0.4%	0.5%	0.7%	0.3%	1.1%	15.0%	5.0%	0.0%	4.8%
9	1.6%	0.5%	0.6%	1.0%	0.6%	1.7%	15.0%	5.0%	0.0%	5.4%
10	3.1%	0.7%	0.9%	1.8%	0.7%	2.5%	15.0%	5.0%	0.0%	6.4%
11	2.9%	0.6%	0.7%	1.7%	0.8%	1.7%	15.0%	5.0%	0.0%	7.4%
12	3.9%	0.9%	1.1%	2.6%	1.0%	3.1%	15.0%	5.0%	0.0%	8.1%
13	5.3%	0.9%	1.2%	3.5%	1.1%	3.7%	15.0%	5.0%	0.0%	8.8%
14	5.7%	0.8%	1.3%	3.6%	1.2%	3.4%	15.0%	5.0%	0.0%	8.2%
15	5.7%	0.7%	1.2%	3.4%	1.4%	2.9%	15.0%	5.0%	0.0%	7.9%
16	4.9%	1.1%	0.9%	2.7%	1.4%	2.6%	15.0%	5.0%	0.0%	7.4%
17	4.0%	1.0%	1.0%	2.0%	1.2%	2.5%	15.0%	5.0%	0.0%	8.7%
18	2.9%	0.8%	0.7%	1.5%	0.8%	2.0%	10.0%	5.0%	0.0%	10.4%
19	2.0%	0.7%	0.6%	1.1%	0.6%	1.4%	10.0%	5.0%	0.0%	11.8%
20	1.5%	0.6%	0.5%	0.9%	0.5%	0.8%	10.0%	5.0%	0.0%	13.7%
21	1.1%	0.4%	0.4%	1.1%	0.4%	0.8%	5.0%	5.0%	0.0%	16.1%
22	1.1%	0.4%	0.3%	0.8%	0.4%	0.8%	5.0%	5.0%	0.0%	16.0%
23	0.8%	0.2%	0.2%	0.6%	0.3%	0.6%	5.0%	5.0%	0.0%	14.5%