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Optimal Demand Response Models with Energy Storage Systems in Smart Grids

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by

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DEDICATION

To my father and my mother, to my borthers and my sisters, to my wife and my kids.

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ABSTRACT

This research aims to develop solutions to relieve system stress conditions in electric grids. The approach adopted in this research is based on a new concept in the Smart Grid, namely demand response optimization. A number of demand response programs with energy storage systems are designed to enable a community to achieve optimal demand side energy management.

The proposed models aim to improve the utilization of the demand side energy through load management programs including peak shaving, load shifting, and valley filling. First, a model is proposed to find the optimal capacity of the battery energy storage system (BESS) to be installed in a power system. This model also aims to design optimal switchable loads programs for a community. The penetration of the switchable loads versus the size of the BESS is investigated. Another model is developed to design an optimal load operation scheduling of a residential heating ventilation and air-conditioning system (HVACs). This model investigates the ability of HVACs to provide optimal demand response. The model also proposes a comfort/cost trade-offs formulation for end users. A third model is proposed to incorporate the uncertainty of the photovoltaic power in a residential model. The model would find the optimal utilization of the PV-output to supply the residential loads.

In the first part of this research, mixed integer programming (MIP) formulations are proposed to obtain the optimal capacity of the (BESS) in a power system. Two optimization problems are investigated: (i) When the BESS is owned by a utility, the operation cost of generators and cost of battery will be minimized. Generator on/off states, dispatch level and battery power dispatch level will be determined for a 24-hour period. (ii) When the BESS is owned by a community for peak shaving, the objective function will have a penalty component for the deviation of the importing power from the scheduled power. MIP problems are formulated and solved by CPLEX.

The simulation results present the effect of switchable load penetration level on battery sizing parameters.

In the second part, a mixed integer programming (MIP) based operation is proposed in this part for residential HVACs. The objective is to minimize the total cost of the HVAC energy consumption under varying electricity prices. A simplified model of a space cooling system considering thermal dynamics is adopted. The optimization problems consider 24 hour operation of HVAC. Comfort/cost trade-off is modeled by introducing a binary variable. The big-M technique is adopted to obtain linear constraints while considering this binary variable. The MIP problems are solved by CPLEX. Simulation results demonstrate the effectiveness of HVAC's ability to respond to varying electricity price.

Then, in the final part of this research, two Benders Decomposition strategies are applied to solve a stochastic mixed integer programming (MIP) formulation to obtain the optimal sizing of a photovoltaic system (PV) and battery energy storage system (BESS) to power a residential HVACs. The uncertainty of PV output is modeled using stochastic scenarios with the probability of their occurrence. Total cost including HVAC energy consumption cost and PV/battery installation cost is to be minimized with the system at grid-connected mode over eight hours subject to a varying electricity price. The optimization problem will find the optimal battery energy capacity, power limit, number of PV to be installed, and expected HVAC on/off states and BESS charging/discharging states for the next eight hours. This optimization problem is a large-scale MIP problem with expensive computing cost.

CHAPTER 1

INTRODUCTION

Several developments in the power and energy industry have been increasingly growing recently to face the challenges arising from the increased power demand by the industrial, commercial and residential loads. Any mismatch between the power demand and power supply can create many difficulties to the power utilities. Smart Grid technology is considered the most important one between those developments which aim to help mitigate those challenges. Smart Grids have provided many opportunities and created on the other side many challenges regarding the power systems security and reliability and efficient operation [1, 2, 3, 4]. Smart Grid simply is a vision that can make effective integration between transmission networks, distribution networks, and various distributed energy sources. Smart Grid accomplishes this integration using intelligent substation and distribution equipment, frequency monitoring devices, and smart sensors. At the customer level, Smart Grid implement intelligent control strategies for operation smart home appliances. One of the smart grid's components is renewable energy sources. Recently, the renewable energy sources have been increasingly growing and penetrating the electric grids. Most of those sources are small decentralized units having variable sizes and connected to power grids. This penetration can threat the reliability of the power grid as its uncertain generation may cause imbalance between supply and demand. The grid operators must ensure to make a backup reserve available in case of emergencies. Therefore, the investments for energy storage systems have been growing and becoming an important part of any smart grid. Some energy storage technologies include flywheel, pumped storage water plants, or compressed air storages. Integrating those technologies with smart grids can mitigate the power fluctuation that could cause serious problem to grid stability. Demand Side Management (DSM) is another function that can be achieved by smart grids. Smart home, smart appliances, and smart meters can help manage loads by shaving loads during the peak hours or by shifting them from peak hours to off-peak hours [5, 6, 7].

1.1 Background

1.1.1 Smart Grid

As stated by the DOEs general report, The Smart Grid: An Introduction, 'a smart grid uses digital technology to improve reliability, security, and efficiency of the electric system from large generation and delivery systems to electricity consumers and a growing number of distributed-generation and storage resources' [2].

The Energy Independence and Security Act of 2007 has given more descriptions about the Smart Grid. Based on these descriptions, Smart Grid can be described as a combination of technologies and strategies that can modernize the power system grids. It can improve several functions such as monitoring, protecting and operating and controlling optimally. It can integrate various parts of the electricity network to enhance the overall performance. All grid levels, generation, transmission, distribution, and customers, can collaborate via many components that Smart Grids adopt and deploy throughout its coverage areas [3].

Smart grids offer many advantages such as: two-way communications, advanced controls, modern sensors, micro-grids and two way power flow. Changes have to be made in the production, distribution, and consumption of electricity, in order to keep up with increased demand. Economically, the electricity industry is one of the largest industrial sectors in the U.S, with the value of assets in excess of trillions of dollars. The number of utilities in the US exceeds 3,273, and provides electricity to over 144 million customers [3], [4],[5]. The primary goal of these utilities is to provide reliable and efficient electricity to consumers. Even with the highest power quality, the direct and indirect losses attributed to power interruptions, voltage sags, surges, etc. are tremendous [5]. Smart grids focus on introducing communication to all components of the grid. If everything is communicating, energy efficiency can be maximized. In addition, a smart grid expands on the ways that power is routed through the grid, and ultimately adjusts pricing of the energy used during peak hours. In essence, DSM is only possible if a Smart Grid system is implemented.

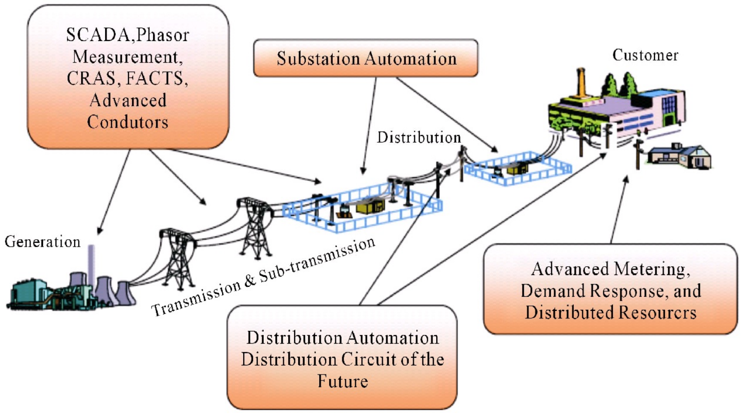

Figure 1.1: Smart grid components ;FACTS 'flexible AC transmission systems' ;CRAS 'centralized remedial action scheme'; [1].

1.1.1.1 Smart Grids Goals

- Providing a model that can allow users to provide new services into the market.
- Establishing a feasible economical model that can provide keys to renew the power grids.
- Maintaining the grid reliability and ensuring its security.
- Providing a model that can support a liberalized market.
- Establishing a model that ensures great renewable energy sources integration.
- Ensuring the best utilization of current power generation.
- Establishing a model that considers the environmental impact.
- Creating a model that encourages more participation from the demand side.

1.1.2 Demand Side Management (DSM)

Utilities always encourage consumers to improve the pattern of their electricity usage. Utilities plan, implement and monitor all those operation activities that can ensure reliable service and encourage customers to participate in programs that help them modify their usage. Those programs are called Demand-side management programs (DSM). Several methods can be used to encourage consumers to participate and be more effective in those programs. Financial incentives method is one tempting way that can make consumers reduce their usage during the peak hours or to shift their usage to later hours which would result in reducing their energy bills or making some money. Utilities also reach out their consumers by through educational programs that can make behavioral change to use electricity. Therefore, utilities do not expect that total energy consumption would be decreased, but they expect they can shift loads from peak hours to off-peak times and this can fill up the valley periods during the day. This modification can help utilities achieve one of the ultimate goals the DMS programs which is to reduce the investment in or defer the need to building more power plants, transmission lines, and distribution networks. A very simple example is the battery energy storage systems usage. These systems can be used to store the energy during the off-peak hours and discharge during peak hours to meet the demand. Today, DSM programs are even more effective in balancing the mismatch between the demand side and supply side in those networks where the renewable energy resources are heavily penetrating and generating intermittent power. Usually DSM is accomplished by various strategies. Two basic strategies are: Developing energy efficient products and systems in order to reduce energy consumption. Load profile shaping is another strategy that can manage the demand and plan the operation in order to better utilize all utility components.

1.1.2.1 Energy Efficiency

Energy efficiency means using less energy without affecting or reducing the service. It is one of DSM aims and can be achieved through using specific efficient appliances, systems, or end-user devices. Energy efficiency strategy can reduce the consumer consumption without even taking consideration of the time during the day or the night and it can induce savings. Some examples of energy efficiency can be seen with the HVACs loads. Those systems can be manufactured with high efficient components and equipped with advanced control methods. The buildings can be efficiently designed with more efficient material including glass window and walls insulations. This can help HVACs to use less energy while maintaining the required service without any change.

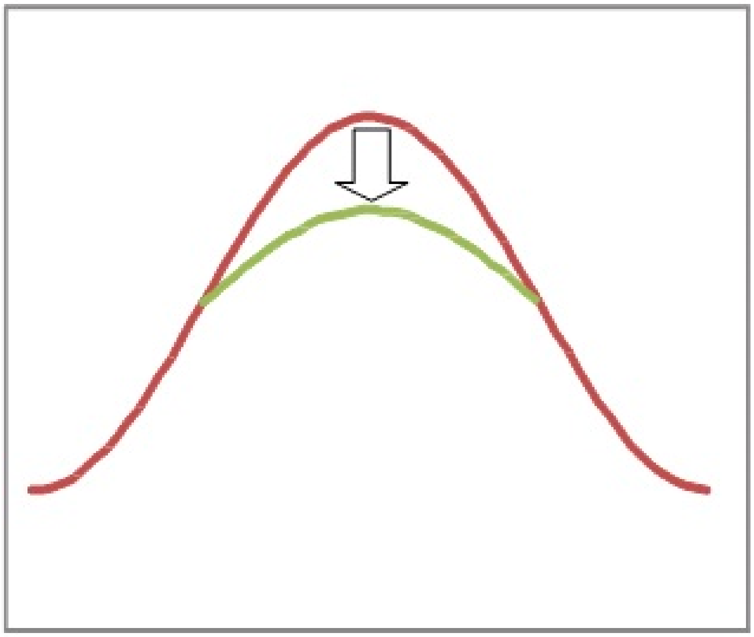

Figure 1.2: Peak clipping.

1.1.2.2 Load Management (Demand Response)

Load management programs have been increasingly growing and in some cases, they can be called Demand Response programs (DR). The main goal of those programs is to manage the power on the demand side via implementing various economic methods. When implementing those programs, the result can be seen in the shape of the load profile [5]. It can be applied at different scales either small or relatively large such as a large community or a region. The demand consumption will be optimized to improve the system load factor. The definition of the load factor is the ratio of the average demand during a defined period over the maximum demand during that defined period. This ratio is between 0 and 1 and the greater this value is, the better the demand management plan is implemented. Therefore, when the load factor value is 1, it means that value is the best. However, this is still impossible in practice. When the load factor value is low, it indicates that there would be great fluctuations in the load profile and that is not preferred by utilities as it will increase their operation costs. Therefore, utilities use several methods that can help improve the load factor and various measures to ensure the grid is secure, reliable and stable.

1. Peak shaving:

   This technique is one of the more traditional forms of load management, it helps the grid operator to shave the peak load by switching off interruptible loads during peak load periods during the day. The most common loads included in the interruptible loads are the controlled thermostatically loads that can be directly controlled by the grid operator or the aggregator. Utilities implementing this practice try to gain a direct control over their customers thermostatically controlled load. The load profile will be affected by this practice and the result of it is shown in Fig. 1.2. Recently, this practice has been a popular method for many utilities when they are trying to achieve great economic dispatch and can help them avoid operating those expensive units to just meet the demand during the peak times. This practice can also be used by those utilities which are not having enough generation to meet the maximum demand during the peak times.

2. Valley filling:

   This technique is also considered as one the common practices used by utilities to achieve great load management. Usually, the daily load profile would show that there are some periods where is less than the daily average demand. Those periods are still costly as the utilities still run their units as they will not simply switch-off those units during those periods and switch them on during the peak periods. The starting-up and shutting-down of units is costly, therefore, the utilities prefer to fill up those periods by increasing the demand by either encouraging people to plan for their usage during those periods. This can be done through making a dynamic energy price that can be high during the peak hours and low during the off-peak hours. Some loads that consumers can plan to use during off-peak periods are water heaters, dish washers, washing machines, or dryers. The load profile will be affected by this practice and the result of it is shown in Fig. 1.3.

3. Load shifting:

   This technique is another practice utilities use to achieve great load management. This practice is a combination of both peak shaving and valley filling practices. Here, consumers

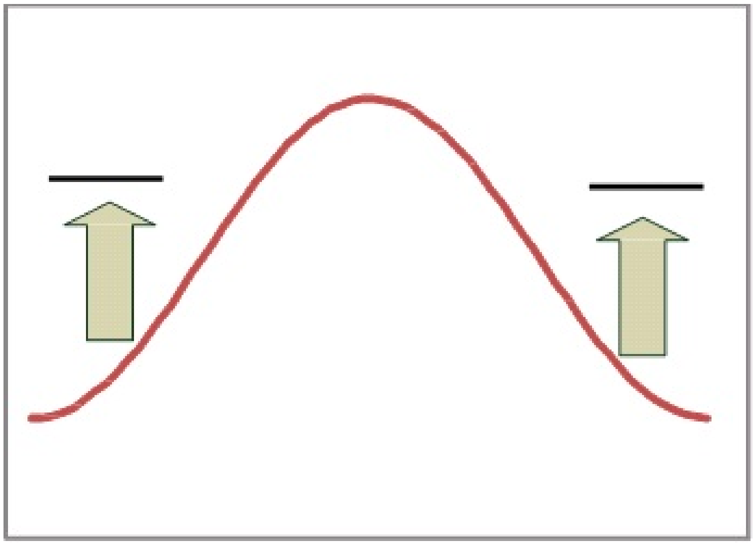

Figure 1.3: Valleys filling.

still use the same daily consumption, however, they need to change their usage pattern. They will shift their usage to be during the off-peak hours instead of peak hours. Utilities can achieve this by creating demand response programs that allow customers to participate and get some incentives or by implementing a dynamic energy price that can make customers change their usage pattern to avoid paying more money. The shape of a load profile using load shifting techniques is given in Fig. 1.4.

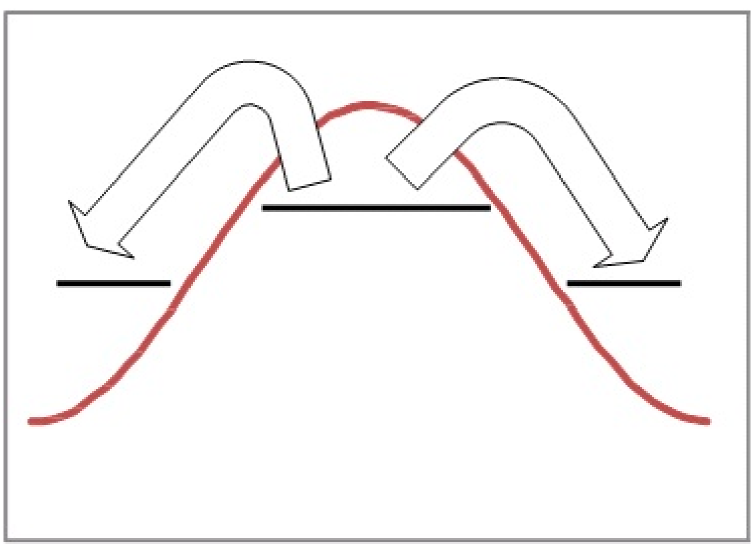

Figure 1.4: Load shifting.

1.2 Energy Storage System

Energy storage has been used for decades in the United States utility grid and now integration of renewables is creating a need for more distributed storage energy. Also, the recent advances in storage technology have led to wider deployment of storage technologies in todays electricity networks. Based on A report released in December 2013 by the United States Department of Energy, at present, the U.S. has about 24.6GW (approx. 2.3 % of total electric production capacity) of grid storage. Europe and Japan have notably higher fractions of grid storage.

1.2.1 Energy Storage and the Smart Grid

A great smart grid must be featured with reliability and security at high level. It must consider all variables and dynamics that can affect demands side or generation side. To develop more intelligent grid, it is really crucial to handle the balancing challenge between demand side and supply side carefully. A smart grid must consider all variables associated with operation and control of the supply sides including the growing renewable energy sources, and all variables associated with the implementation of the demand response programs in the demand side. The balancing challenge can be tackled by utilizing amount of energy storage units throughout the smart grid.

1. Peak clipping in Low Voltage (LV) grid:

   Energy storage systems can be used to store the energy during the off-peak hours when the energy price and demand is low; then, it can dispatch power during the peak hours when the energy price and the demand is high. This can be implemented in the low voltage networks and can help the system operators and utilities to defer building power plant and transmission lines.

2. Load shifting in LV grid:

   Energy storage systems can allow grid operators to shift loads during anytime the grid could go through any overloaded event, and this can this can mitigate and reduce the probability that fatal faults can occur and produce unwanted damage to the power grid devices.

3. Integration of renewable energy into the grid:

   Energy storage systems can be integrated with a renewable source to solve the intermittent issue and to form a remote area power supply. It can allow the grid operator to minimize the fluctuation of the supply resulting from faults or from the unreliable renewable sources. This can also give the grid operators more flexibility to control the voltage level and make the grid more stable. This function can help the system operators and utilities to defer building power plant and transmission lines.

4. Frequency regulation:

   Due to the increasingly growing renewable generation and the nature of uncertainty associated with such sources, the grid frequency is highly expected to be instable in case that the grid is not prepared for such penetration. When utilized with grids, the energy storage systems can ensure the availability of reserve power generation that can help mitigate any frequency instability events. Therefore, the energy storage systems are considered to be a great source to allow the grid operator to control the frequency within the defined limits.

5. Voltage control:

   The voltage level of the grid must be maintained with a specific limits and any instability could lead to serious and fatal faults. The energy storage systems can achieve great performance controlling the voltage level by storing the energy during the time when and voltage is high and releasing it during the time when voltage level is low.

1.3 HVACs Loads

The main characteristic of HVACs loads is ability to work like energy storage systems. Here the main objective of using HVACs loads in DSM is to switch those loads on and store the thermal energy during off-peak hours and switch them off during the peak hours and get benefits of the thermal stored energy. Aggregating a large number of those unites can benefits the grid to achieve a great load management shaping the load profile using any technique of the above mentioned.

1.4 Problem Identification

Electricity supply and demand must be balanced all the time in an electricity grid. Failures within the grid, instability or sever voltage fluctuations are consequences for any significant imbalance between supply and demand. The imbalance could occur because of shortage in supply side. In addition, with the increasing and rapid growth in renewable resources and due to their uncertainty nature, it is highly expected to observe imbalance if the utilities are not taking the necessary precautions of dealing with such uncertain variable sources. Therefore, utilities always optimally size their generation to meet and match the peak demand plus the required spinning reserve to ensure more reliability. In some cases the peak demand period is short; however, the utilities still have to meet this demand to avoid any imbalance. Due to the high costs associated with starting-up and shutting-down generation units, utilities are forced to keep some units running but generating their minimum output during the periods when the demand is low. Utilities always try to find solutions to minimize the total operating costs by determining the optimal schedule for dispatching the generation units. Another solution for this problem is load shedding and paying penalties to consumers in order to reduce the peak demand. Utilities may also consider other solutions by utilizing energy storage systems to store energy during the off-peak hours where the demand is low whereas supply is excessive and then dispatch it when during the peak hours when the demand is high. Utilities may also investigate creating demand response programs that can allow customers to participate by modifying their usage pattern or allowing the utilities to control over their loads such as HVAC loads. Customers can get engaged in demand response programs such as incentive based programs where they receive money for switching off their loads during specific events or price based programs where the utilities use pricing mechanism depending on the supply and demand quantity.

1.5 Scope of Work

1.5.1 Energy Storage System Planning

The objective here is to find the optimal size of the energy storage system to be installed in utility to minimize the total operating cost while meeting all load demand considering that the utility has the option to purchase power from another grid at varying energy price.

1.5.1.1 Tasks

1. Energy Storage System Applications in Utilities (Supply-Side) The Objective here is to find the optimal size of the energy storage system to be installed in utility to minimize the total operating cost while meeting all load demand considering that the utility has the option to purchase power from another grid at varying energy price

   (a) Determine the optimal unit commitment schedule considering the quadratic cost function of the thermal generating units and the associated costs with starting-up and shutting-down of the units.

   (b) Determine the optimal size of the energy storage system and the optimal charge/discharge power schedule

   (c) Determine the optimal purchased power which can be imported from another grid

   (d) Determine the optimal number of the interruptible loads and the optimal time they would be interrupted.

2. Energy Storage System Applications in Communities (Demand-Side) A Community can participate in Demand Response program by being committed to purchase constant power for all periods of the day from the grid at competitive price. The community will pay a penalty for any deflection from that constant power. Now, the objective is to minimize the total cost paid by the community to meet its demands which is varying throughout the day.

   (a) Determine the constant power which can be purchased from the grid.

(b) Determine the optimal size of the energy storage system which can be installed in the community and determine the optimal charge/discharge power schedule.

(c) Investigate the effects of different amounts of penalties on the optimal size of the battery and the total cost.

1.5.2 Modeling HVACs for DSM

Electricity service providers consider demand response (DR) and DSM programs to better manage the electricity usage patterns of customers. The biggest percentage of electrical loads of most commercial facilities, such as large office buildings, hotels, etc. is comprised of the lighting and HVACs. Here, the objective is to investigate the potential benefits to either utilities or consumers from optimizing the operation of HVACs

1.5.2.1 Tasks

1. Develop mixed integer programming to find the optimal operating schedule of HVACs in order to minimize the total operating cost.

2. Investigate the response of HVACs loads when utilities aim to shave peak demand.

3. Investigate the effect of adding battery bank to the system which can store energy from the grid and supply it to HVACs when needed.

4. Adjust the formulation to provide optimal comfort/cost trade-offs for the resident based on the varying prices of the energy.

1.5.3 Operation Considering Stochastic Renewable Energy Sources

HVAC loads account for a large portion of the peak loads that could reach to 40%-60% of the loads in commercial and residential buildings. Also during the day time, there is much of unexploited solar energy that could be utilized to enhance DSM functions. Therefore, it is essential to use Photovoltaic cells (PV) to harvest the sun energy and convert it into electricity that can power the HVAC units. However, the stochastic nature of intermittent PV output complicates the integration of operation and planning purposes. Here, the objective is to address the uncertainty issues which are associated with the PV-output and to investigate the potential benefits of optimizing PV-BESS to provide HVACs with power.

1.5.3.1 Tasks

1. Address the uncertainty issues of PV-output through developing different PV-output scenarios using real world data.

2. Develop Benders Decomposition formulation for solving a Stochastic Mixed Integer Programming to find the optimal size of PV-BESS considering purchasing power from the grid at a varying energy price.

3. Determine the optimal operating schedule status ON-OFF of HVACs

4. Determine the optimal Charge/Discharge schedule of PV-BESS.

5. Compare the results of the stochastic models to the results of the deterministic models.

CHAPTER 2

LITERATURE REVIEW

2.1 Research on Demand Response Applications with Storage Energy

Authors in [8] have presented a sizing methodology based on peak shaving similar as the industry practice illustrated in Fig. 1.2. In [9], Monte Carlo simulation methods are used to find the suitable size for a BESS while meeting the demand and considering outages of generators. Computational simulations were used in [10] to find the optimal size of battery systems for mitigating the fluctuations of a PV power plant output. Optimization problems related to a battery energy storage system (BESS) operation have been formulated for BESS operation. For example, in [11], a mixed integer linear programming was introduced to find the optimal operation scheduling of a BESS in order to reduce the effect of intermittence of the renewable generation units. The size of the battery is assumed known and the objective function does not include battery cost. An optimization problem to find 24-hour dispatch pattern for a flow battery is presented in Reference [12]. The flow battery is used for peak shaving and the objective function is the sum of the power deviation between net load profile and the scheduled power. The optimization program considers battery constraints but does not consider other decision variables. Variety of other optimization methods can also be found in the literature. In [13] and [14], dynamic programming was used to find the optimal size of the BESS in a power system. In [15], linear programming was used to optimize the energy storage dispatch schedule. Particle swarm optimization was used in [16] to determine the optimal schedule a BESS dispatching for an end user consuming energy at a varying price and having a wind power system. In [17], the authors developed a model to determine the optimal operating schedule for energy storage systems. They used a method that combines the genetic algorithm and linear programming. Many problems related to the scheduling of the charging and discharging of an ESS have been studied recently [18, 19, 20, 21]. Various optimization techniques can be applied to the operation of BESS. The most frequently used method is dynamic programming, which was used by the author in [22]. They tried to minimize electricity cost for an BESS with a given battery capacity, without unnecessarily reducing battery life. The author in [23] aimed to minimize the capital cost of an BESS subject to user demand and prices, as a Markov decision process, which can be solved using dynamic programming. In [24], the author addressed the optimal BESS control problem from the point of view of a utility operator and solved the off-line problem over a finite period by dynamic programming. In [25], the author investigated stochastic dynamic programming for energy management of a hybrid BESS for electric vehicles. They aimed to control the power flow to the BESS online, while taking into account the stochastic influences of traffic and the driver. The author in [26] applied adaptive dynamic programming to the management of a residential BESS, with an emphasis on domestic electricity storage systems. Their scheme was designed to learn during operation as the environment of the BESS changes unpredictably. While those paper investigated the optimal scheduling for BESS charging-discharging, they did not consider the impact of the battery efficiency. In that paper, we investigated the impact of the battery charging and discharging efficiencies by formulating mixed integer linear programming model and implementing big-M technique to decompose the battery dispatching in two variables representing charging power and discharging power instead of considering only one variable denoting the battery in charging mode when that variable is positive and in discharging mode when it is negative.

2.2 Research on Demand Response Applications with Residential Loads

Regarding HVAC optimal operation models, several models have been developed to determine the potential benefits when implementing the demand side management and demand response strategies. Authors in [27] proposed an analysis for demand response that considers modeling loads as single components rather than lump model. They argued that when considering loads as single components, this would give more realistic operation for some complex components which have so complicated operational constraints. Therefore, the authors developed a dynamical model for HVAC loads based on simulations and performance tests on an actual unit. The HVAC parameters are collected based on historical data. Those models are used to investigate the impacts that HVAC loads can provide to demand side management programs. Authors in [28] proposed an algorithm that can help demand response programs aggregators automatically schedule the energy consumed by thermostatically controlled loads and make better decisions to dispatch their events. The authors used Karush Kuhn Tucker (KKT) conditions to model the optimization problem. Here, the authors did not consider practical operating constraints when modeling HVAC models. This study did not investigate the impacts of the optimal scheduling on the demand response or on the consumers comfort settings. In [29], the authors have investigated a design of a residential HVAC system whose objective function is to respond to energy received from the utility to determine an optimal plan for trading off between comfort and cost. They used a stochastic dynamic programming to develop an HVAC control strategy where it can permit the controller to make the best decision responding to varying power prices. Then, the thermal dynamics of the HVAC system and the house were represented and simulated using physics-based models to be more practical for the system control purposes of the residential HVAC system. Finally, the economic effects of this trade-off formulation were investigated to explore their feasibility. In [30], the possibility that aggregating a large number of HVAC loads can provide intra-hour load balancing services was investigated using a direct load control algorithm. In [31], a linear-sequential-optimization-enhanced, multiloop algorithm was proposed to solve the appliance commitment problem concerning the thermostatically controlled household loads. Electric water heater was modeled to simulate those loads. In [32], the authors investigated the efficiency of a hybrid system combining renewable energy source and battery system to power a controllable HVAC load. They used a genetic algorithm approach to minimize the cost and increase the efficiency.

2.3 Research on Demand Response Applications with Hybrid PV/Energy Storage/HVAC System

Addressing the issues of uncertainty of renewable energy has been studied in the literature, e.g., [33, 34, 35, 36]. In the aforementioned papers, optimal design and operation of wind/solar hybrid systems is discussed. In [32], the authors investigated the feasibility of meeting controllable HVAC loads by a hybrid energy system combining renewable energy sources and battery energy system. This study did not consider on/off status. To address uncertainty, stochastic programming problems are usually formulated where numerous scenarios with probability are created. This results in large-scale optimization problems. Heuristic method, e.g., genetic algorithm, is sought in [32] to solve the problem. A major disadvantage of heuristic methods is that they may arrive at a local optimal solution. To complicate the matter, when optimal sizing and HVAC on/off are considered, integer variables are introduced. This makes problem solving a challenging issue. Prior research related to stochastic MIP can be found in [37, 38]. Branching and bound solving strategy is applied in [37], while Benders decomposition is applied in [38]. In [37], two-stage stochastic programming is employed to determine the optimal scheduling problems for processes of chemical batch. In [39], the authors employed two-stage stochastic programming to determine the optimal offering strategy plans that wind generation plant should consider for its production. The nature of uncertainty of wind power and the uncertainty of energy market price was considered. In [40], Time-of-use (TOU) rates are designed to find the optimal demand response programs options. The authors used two-stage stochastic MIP to accomplish the study. In literature, there are several studies that investigated the battery scheduling problems. In [41], a deterministic mixed integer programming is used to develop an optimal charging schedule by solar panels. In [42], the authors developed an optimal discharging schedule for battery system based on a decision-making algorithm. Commercial solvers such as CPELX or Gurobi are usually adopted. However, very long computing time is expected. For example, in [36], the model was run using 4 parallel CPU threads on a 256 GB RAM server running GAMS 23.0.2 and CPLEX 11.2.1 and the maximum execution time is 10 hours. The second option is heuristic methods. Heuristic methods, e.g., genetic algorithm [32], has the similar scalability issues. The third option is to use commercial solvers through customized algorithm. For example, branching and bound solving strategy is applied in [37] while Benders decomposition is applied in [38]. Compared to branching and bound method, Benders decomposition is a known efficient algorithm to handle large-scale mixed-integer problems. Benders decomposition has been applied in many power system applications, e.g., unit commitment problems considering wind [38] or transmission constraints [43], transmission planning considering wind [44]. The essential technique is to decompose decision variables into multiple sets [45], e.g., a set of mixed integer variables and a set of continuous variables. For each set of variables, optimization solving will be conducted.

2.4 Research on Large-scale MIP Solving

Stochastic Mixed Integer Programming problem is considered one of the Large-scale optimization problems. Those Large-scale optimization problems are investigated in the literature review widely using different methods. Some of these methods are heuristics that have been applied to large scale problems to determine different objectives. In [46], the author applied simulated annealing to determine the optimal size of a PV/wind/ hybrid energy system with battery storage. In [47] the author applied genetic algorithm to determine the optimal power generated from a renewable generation system in an isolated island considering the nature of the uncertainty. In [48], Tabu search method was used to find the optimal size of small hybrid power systems. A major disadvantage of heuristics methods is that they may reach to local optimal solution and here the solution quality is not. That may lead to adopt a solution but it is not the optimal one. Those problems can still be formulated and solved using commercial MIP. However, those solvers are available for many researchers, need large computers, and must be paid at high cost. There are other methods which are more applicable and used within the literature. Those methods depend on the cutting plan algorithms. In [49] , algorithms based on Benders decomposition method) are considered to be the most effective methods to be applied and used to tackle various SMIP problems. An enhancement and improvement strategies have been applied to those algorithms to reach to better solution. Pareto-optimal cuts in [50] are among those enhancements. In [51], the author modified the previous methods and introduced more efficient optimality cuts with higher quality. In [52], another modification is introduced to give more efficient optimality cuts. Here, a strategy to create maximum feasible region for multi subproblems and that can reduce the number of feasibility cuts generated in Benders algorithm.

2.4.1 General Benders Decomposition

In this section the structure of the general bender decomposition is shown. Model.2.1 describes the original problem

$$\begin{aligned} \min_{x,y} \quad & c^T x + q^T y \\ \text{s.t.} \quad & Fx + Wy \leq b \\ & x \in X \\ & y \geq 0 \end{aligned} \tag{2.1}$$

c,x are n_1 vectors; q,y are n_2 vectors;b is m vector; F is an $(m \times n_1)$ matrix; W is an $(m \times n_2)$ matrix. Now, the original problem can be decomposed in two problems. The problem(2.2) describes the master problem:

$$\begin{aligned} \min_{x} \quad & Z_{lower} \\ \text{s.t.} \quad & Z_{lower} \geq c^T x \\ & x \in X \end{aligned} \tag{2.2}$$

The subproblem structure is described by primal and and dual structures. The primal structure is described by (2.3)

$$\begin{aligned} \min_{y} \quad & q^T y \\ \text{s.t.} \quad & Wy \leq b - Fx \\ & y \geq 0 \end{aligned} \tag{2.3}$$

while the dual structure is described by (2.4)

$$\begin{aligned} \max_{u} \quad & [-(b - F(x))^T u] \\ & W^T u \geq -q \\ & u \geq 0 \end{aligned} \tag{2.4}$$

For general bender decomposition, (2.2) is solved to find the optimal solution x and then proceed to (2.3) to solve it with the obtained optimal values of x in (2.2). Here, the subproblem could be infeasible. In this case, a feasibility cut is generated and added to the master problem. The steps to do that are as the following:

$$\begin{aligned} \min_{y,s} \quad & 1^T s \\ & Wy + 1s \geq b - Fx \\ & s \geq 0 \end{aligned} \tag{2.5}$$

For generating this cut, u^r,the dual associated with this problem, must be calculated. The general form of this cut is:

$$[(b - Fx)^T u^r] \leq 0 \tag{2.6}$$

In the case, the problem is feasible, then Z_{upper} is calculated and the convergence behavior is tested. If the convergence is not approached, then an optimality cut is generated and added to the master problem. The optimality cut is generated from the following form:

$$Z_{lower} \geq c^T x + (b - Fx)^T u^p \tag{2.7}$$

In the following section, a simplified example illustrated in [53] is introduced to give the reader more understanding about applying Benders decomposition algorithm.

2.4.2 Benders Decomposition Example

In this example a general Benders decomposition is applied to Security Constraint Unit Commitment (SCUC) problems in power system. SCUC can be decomposed in two separate structures. The first structure is a mixed integer programming problem and the second structure is linear programming. Those structures are called master problem and subproblem structures. The master problem is solved first and its optimal solution will be used to solve the subproblem and the convergence is tested. In case the subproblem is infeasible, then an infeasibility cut is generated and added to the master problem. In case the subproblem is solved but there is no convergence, then an optimality cut is generated and added to the master problem. This process will continue until the convergence is achieved. The procedures to solving this problem are explained in details.

2.4.2.1 Objective Function

$$\min_{P_{i,t},\alpha_{i,t},\beta_{i,t}} \sum_{t=1}^{T} \sum_{i=1}^{g} C_i(P_{i,t}) + st_i\alpha_{i,t} + sd_i\beta_{i,t} \tag{2.8}$$

2.4.2.2 Constraints

1. Power balance

$$\sum_{i=1}^{N_g} P_{i,t} = D_t \tag{2.9}$$

2. Generators Limits

$$\underline{P}_i I_{i,t} \leq P_{i,t} \leq \overline{P}_i I_{i,t} \tag{2.10}$$

$\underline{P}_i$ refers to the minimum power output of the $i-th$ generator.

$\overline{P}_i$ refers to the maximum power output of the $i-th$ generator.

3. Start-up/Shut-down limits

$$st_i\alpha_{i,t} - sd_i\beta_{i,t} = I_{i,t} - I_{i,t-1} \tag{2.11}$$

$P_{i,t}$ refers to power dispatched by the $i-th$ generator at $t-th$ hour.

$\alpha_{i,t}$ is a binary variable to equal 1 if $i-th$ generator is started at $t-th$ hour.

$\beta_{i,t}$ is a binary variable to equal 1 if $i-th$ generator is shut down at $t-th$ hour.

$I_{i,t}$ is a binary variable to equal 1 if $i-th$ generator is ON at $t-th$ hour.

C_i refers to cost of producing 1 kW from the $i-th$ generator.

st_i refers to cost of starting the $i-th$ generator.

sd_i refers to cost of shut down the $i-th$ generator.

4. Network constraints

$$-F_{k,m} \leq f_{km,t} \leq F_{k,m} \tag{2.12}$$

$F_{k,m}$ refers to the maximum line capacity from bus k to bus m.

$f_{km,t}$ refers to the power flow on the line from from bus k to bus m at $t-th$ hour.

2.4.2.3 Procedures to Solving the Problem

In the first step, we form the master problem and find its optimal solution as follows:

$$\min_{\alpha_{i,t},\beta_{i,t}} Z_{lower} \tag{2.13}$$

subject to:

$$Z_{lower} \geq \sum_{t=1}^{T}\sum_{i=1}^{g} st_i\alpha_{i,t} + sd_i\beta_{i,t} \tag{2.14}$$

$$st_i\alpha_{i,t} - sd_i\beta_{i,t} = I_{i,t} - I_{i,t-1} \tag{2.15}$$

constraint(2.15) ensures that any unit that is online can be shut down and can't be started up. It also ensures that any unit that is offline can be started up but not shut down where:

$\alpha_{i,t}$ is a binary variable to equal 1 if $i-th$ generator is started at $t-th$ hour.

$\beta_{i,t}$ is a binary variable to equal 1 if $i-th$ generator is shut down at $t-th$ hour.

$I_{i,t}$ is a binary variable to equal 1 if $i-th$ generator is ON at $t-th$ hour.

$$\sum_{i=1}^{g} P_{i,max} * I_{i,t} \geq D_t + R_t \tag{2.16}$$

In the second step, we form the subproblem and use the obtained optimal solution for the integer variables from the master problem to solve and find the optimal solution for the other variables. There are going to be a subproblem for each hour:

$$\min_{P_{i,t}} w = \sum_{i=1}^{g} C_i(P_{i,t}) \tag{2.17}$$

$$\sum_{i=1}^{N_g} P_{i,t} = D_t \tag{2.18}$$

$$-P_{i,t} \leq \underline{P}_i I_{i,t} \tag{2.19}$$

$$P_{i,t} \leq \overline{P}_i I_{i,t} \tag{2.20}$$

$$-F_{k,m} \leq f_{km,t} \leq F_{k,m} \tag{2.21}$$

In this step, the subproblem could be infeasible when the available power cannot meet the total demand. In this case, a feasibility cut is generated and added to the master problem. In the case, the problem is feasible, then Z_{upper} is calculated and the convergence behavior is tested. If the convergence is not approached, then an optimality cut is generated and added to the master problem. For the SUCU problem, the feasibility is checked for each hour t. This can be accomplished by checking if the decision variables made in the master problem can provide enough power for the demand or not. So, the loss load or the curtailed load is minimized in an optimization model and if it is greater than zero, that means the decision variables made in master problem are not feasible for the demand. Now, model 2.17-2.21 can be rewritten as following:

$$\min v_t = \sum r_t \tag{2.22}$$

$s.t$:

$$\sum_{i=1}^{N_g} P_{i,t} = D_t + r_t \tag{2.23}$$

$$-P_{i,t} \leq \underline{P}_i I_{i,t} \tag{2.24}$$

$$P_{i,t} \leq \overline{P}_i I_{i,t} \tag{2.25}$$

$$-F_{k,m} \leq f_{km,t} \leq F_{k,m} \tag{2.26}$$

We assume that $\underline{\lambda}$ and $\overline{\lambda}$ are the dual variables associated with constraints 5.11a and 2.25 If v_t is greater than zero then an feasibility cut is generated based on the following:

$$v_t + \sum_{i=1}^{N_g} \overline{\lambda}.\overline{P}_i(I_{i,t} - \hat{I_{i,t}}) - \underline{\lambda}.\underline{P}_i(I_{i,t} - \hat{I_{i,t}}) \leq 0 \tag{2.27}$$

If v_t equals zero then the problem is feasible and we proceed to the check the optimality problem. We assume that $\underline{\pi}$ and $\overline{\pi}$ are the dual variables associated with constraints 5.11a and 2.25. The optimality cut is formed as the following

$$Z_{lower} \geq \sum_{t=1}^{T}\sum_{i=1}^{g} st_i\alpha_{i,t} + sd_i\beta_{i,t} + \sum_{t} \left\{ w_t + \sum_{i=1}^{N_g} \overline{\pi}.\overline{P}_i(I_{i,t} - \hat{I_{i,t}}) - \underline{\pi}.\underline{P}_i(I_{i,t} - \hat{I_{i,t}}) \right\} \tag{2.28}$$

In the third step, the master problem with the added constraints from step 2 will be solved and Form the subproblem and use the obtained optimal solution for the integer variables from the master problem to solve and find the optimal solution for the other variables. There is going to be a subproblem for each hour.

CHAPTER 3

BATTERY STORAGE SYSTEMS FOR DEMAND RESPONSE APPLICATION

3.1 Introduction

In this chapter[1], A mixed integer programming formulation (MIP) is proposed to obtain the optimal load operation scheduling of a Residential Heating Ventilation and Air-Conditioning System (HVAC) to minimize the total cost of the HVAC energy consumption under varying electricity prices. A simplified model of a space cooling is used while considering the thermal energy. Three optimization problems will be investigated: (i) When the HVAC is adjusted to respond to the varying price and satisfying all comfort settings (ii) When the HVAC is adjusted to provide optimal comfort/cost trade-offs for the resident based on the varying prices of the energy (iii) When a battery energy storage system BESS is installed and can supply the HVAC with power. HVAC on/off states, BESS states will be determined for a 24-hour period for each case where it applies. MIP problems will be formulated and solved by CPLEX. The simulation results present the effect of HVAC it can have on the load profile such as peak shaving or load shifting. It also presents the effect of the battery on the total cost of consumption.

Advanced energy storage systems range from flywheel based energy storage to batteries (Lithium Ion, Nickel Metal Hydride, etc.). Large-scale battery storage is now attracting considerable interest. For example, Duke Energy installed a 36 MW battery storage system at the 153 MW Notrees wind power project near Kermit Texas [54] . The important role of a battery energy storage system (BESS) is listed as follows [55, 56]. (i) A BESS can help eliminate the need for a peaking generator. A peaking generator is very expensive and is only used when demand is at its highest. (ii) A BESS can be integrated with a renewable source to solve the intermittent issue and to form a remote area

[1]This chapter was published Energy Systems, Springer, vol.5, no.4. Permission is included in Appendix B.

power supply. (iii) A BESS can also provide backup energy when a blackout occurs by pumping the grid with stored electrical energy.

The size of a BESS is determined by both the power limit (C_b) and the energy limit (E_b). To determine the size of a BESS, there are couple of ways.In [57], a battery is sited along with a 1.6 kW Photovoltaic (PV) to generate constant output power. The mean value of the PV is first found for a 24-hour period. The power size of the battery is then determined by the difference between the maximum PV output or minimum PV output versus the mean value. The energy size of the battery is determined by integrating the expected battery discharging power over the valley period or the charging power over the peak period. Fig. 3.1 gives an illustration diagram to show the valley period and the peak period. The author in [8] presented sizing methodology based on peak

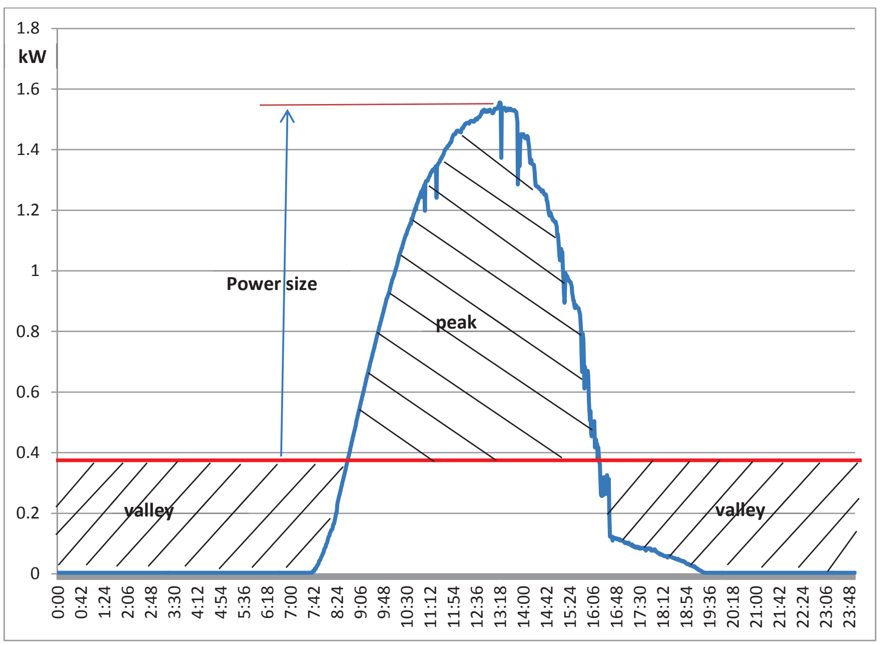

Figure 3.1: Peak and valley period for a battery sited with a 1.6 kW PV panel.

shaving similar as the industry practice illustrated in Fig. 3.1. In [9], Monte Carlo simulation methods are used to find the suitable size for a BESS while meeting the demand and considering outages of generators. Computational simulations were used in [10] to estimate battery capacity for suppression of a PV power plant output fluctuations.

Optimization problems related to a battery energy storage system (BESS) operation have been formulated for BESS operation. For example, in [11], a mixed integer linear programming was introduced to find the optimal operation scheduling of a BESS in order to reduce the effect of intermittence of the renewable generation units. The size of the battery is assumed known and the objective function does not include battery cost. An optimization problem to find 24-hour dispatch pattern for a flow battery is presented in Reference [12]. The flow battery is used for peak shaving and the objective function is the sum of the power deviation between net load profile and the scheduled power. The optimization program considers battery constraints but does not consider other decision variables.

Variety of other optimization methods can also be found in the literature. In [13] and [14], dynamic programming was used to find the optimal size of the BESS in a power system. In [15], linear programming was used to optimize the energy storage dispatch schedule. Particle swarm optimization was used in [16] determine the optimal schedule a BESS dispatching for an end user consuming energy at a varying price and having a wind power system. In [17], the authors developed a model to determine the optimal operating schedule for energy storage systems. They used a method that combines the genetic algorithm and linear programming.

The focus of this work is to adopt mixed linear integer programming to solve a battery sizing problem. Due to the availability of commercial solver such as CPLEX, optimization problems with a large dimension of decision variables can be solved in a fast way. Therefore, using mixed linear integer programming, we can make decision for a comprehensive problem. In this work, two types of applications will be investigated: utility application and demand side application. For each type of application, optimal size for a BESS will be decided. For the utility side applications, the main objective is to minimize the total operating cost of the utility considering switchable loads. For the demand side applications, a community with a 24-hours load profile is considered. The community purchases scheduled power from the utility and pays penalty if the imported power deviates from the scheduled imported power. The contribution of this work is twofold:

1. The studied BESS sizing problem is comprehensive and of practice value. This research considers a BESS, generators, controllable loads, and dynamic pricing. Two practical operation

problems are formulated based on utility point of view to save cost and based on consumer's point of view for peak shaving.

2. Mixed integer programming models for BESS sizing are developed and solved. Compared to many other model formulations [58, 59], where a BESS's size (power and energy) is treated as parameters and a battery's cost is not included in optimization model, in this work, battery's power size and energy size are treated as decision variables. Using the developed models, utilities can make decision to choose a suitable energy and power size for a battery system to save operation cost while considering cost of battery itself.

The chapter is organized as follows: The optimization model for the utility application is presented in Section 3.2. The optimization model for the demand application is presented in Section 3.3. Case studies and numerical examples are shown in Section 3.4. The conclusion of the chapter is presented in Section 3.5.

3.2 Utility Applications: Minimizing Operation Cost with a BESS and Switchable Loads

3.2.1 Optimization Problem

The objective function is to minimize the total cost over a horizon N, including cost of the dispatched power from the generators (P_i), the cost of the imported power from other areas (P_{in}), and the cost of the battery to be installed in the system. The battery cost includes cost related to its converter (power size) and the cost of its storage unit (energy size) [60]. In this research, we choose $\beta_1 = \$.20/kW$, while $\beta_2 = \$.25/kWh$. The battery cost is expressed as:

$$\beta_1 C_b + \beta_2 E_b \tag{3.1}$$

β_1 refers to the cost of 1 kW rating of the BESS;

β_2 refers to the cost of 1 kWh rating of the BESS.

The switchable loads are assumed to have same size and there are N_s of them. Status of the $k-th$ switchable load at $j-th$ hour is notated by:

$$W_{lk,j} = \begin{cases} 1 & \text{offline} \\ 0 & \text{online} \end{cases} \tag{3.2}$$

3.2.2 Decision Variables

In this optimization problem the vector of the decisions variables is as follows:

$$X = [\cdots P_{in,j} \;\; P_{b,j} \;\; C_b \; E_b \; P_{im,j} \; W_{gi,j} \; W_{lk,j} \cdots]^T \tag{3.3}$$

The decision variables for the optimization problem are listed as follows:

- $P_{i,j}$ refers to the dispatched power from the $i-th$ generator at the $j-th$ hour.
- $P_{b,j}$ refers to the discharged from or charged to the battery system at the $j-th$ hour.
- $P_{im,j}$ refers to the imported power at the $j-th$ hour.
- C_b refers to the power rate of the battery energy system.
- E_b refers to the energy rate of the battery energy system.
- $W_{gi,j}$ refers to the binary variable that is equal to 1 if the generator $i-th$ is online and 0 otherwise.
- $W_{lk,j}$ refers to the binary variable that is equal to 1 if the switchable load $k-th$ is offline and 0 otherwise.

3.2.3 Objective Function

The objective function is as follows:

$$\min_{\substack{P_{i,j},P_{b,j},W_{gi,j} \\ W_{lk,j},C_b,E_b,P_{in,j}}} \quad \sum_{j=1}^{N} \left(\sum_{i=1}^{N_g} C_i(P_{i,j}) + \lambda_j P_{in,j} + \left(\sum_{k=1}^{Ns} \alpha W_{lk,j} \right) \right) + \beta_1 C_b + \beta_2 E_b \tag{3.4}$$

N_g refers to the number of generator.

N_s refers to the number of switchable loads.

N refers to the number of hours.

i is the index of the generator.

j is the index of the hours.

k is the idex of the switchable loads.

C_i refers to the quadratic function of the production cost of the $i-th$ generator.

λ_j refers to the price of the imported power at the $j-th$ hour.

α refers to the penalty for switching switchable loads off.

In this research, the size of a switchable load is 3kW. The penalty of turning off 3kW switchable load (α) is given as \$0.33/kWh. This value is based on the evaluation of the average value of the electricity and also based on trying different penalty. Given the average electricity is 0.25 cent/kWh, we choose the penalty to be \$1 to turn off a 3-kW switchable load for each hour.

3.2.4 Constraints

The optimization problem is subject to the following constraints:

1. Power balance

$$\sum_{i=1}^{N_g} P_{i,j} + P_{b,j} + P_{in,j} = D_j - (\sum_{k=1}^{N_s} L_s V_{k,j}) \tag{3.5}$$

L_s refers to the power size of each switchable load.

2. Generators Limits

$$\underline{P}_i W_{gi,j} \leq P_{i,j} \leq \overline{P}_i W_{gi,j}, \tag{3.6}$$

$\underline{P}_i$ refers to the minimum power output of the $i-th$ generator.

$\overline{P}_i$ refers to the maximum power output of the $i-th$ generator.

3. Ramping Constraints The generators outputs are constrained by ramp-up and ramp-down rates. They also are constrained by startup ramp rates and shutdown ramp rates.

$$P_{i,j} \leq P_{i,j-1} + RU_i W_{gi,j-1} + SU_i[W_{gi,j} - W_{gi,j-1}] + \overline{P}_i[1 - W_{gi,j-1}] \tag{3.7}$$

$$P_{i,j} \leq \overline{P}_i W_{gi,j+1} + SD_i[W_{gi,j} - W_{gi,j+1}] \tag{3.8}$$

$$P_{i,j-1} - P_{i,j} \leq RD_i W_{gi,j} + SD_i[W_{gi,j-1} - W_{gi,j}] + \overline{P}_i[1 - W_{gi,j-1}] \tag{3.9}$$

RU_i refers to ramp-up rate.

RD_i refers to ramp-down rate.

SU_i refers to start up ramp rate.

SD_i refers to shutdown ramp rate.

4. Minimum Up and Down Time Constraints

$$\sum_{n=j}^{j+UT_i-1} W_{gi,n} \geq UT_i \left[W_{gi,j} - W_{gi,j-1}\right] \tag{3.10}$$

$$\sum_{n=j}^{j+DT_i-1} [1 - W_{gi,n}] \geq DT_i \left[W_{gi,j-1} - W_{gi,j}\right] \tag{3.11}$$

UT_i refers to minimum up time of the $i-th$ generator.

DT_i refers to minimum down time of the $i-th$ generator.

5. Power rating limits of battery energy system

$$-C_b \leq P_{b,j} \leq \ C_b \ (j = 1, ..., N) \tag{3.12}$$

6. Energy rating of the battery energy system

$$\underline{E_b} \leq E_0 + \sum_{j=1}^{n} P_{b,j} \leq \overline{E_b}, \ (n = 1, ..., N-1) \tag{3.13}$$

$\underline{E}$ refer to the minimum energy limit of the battery unit.

$\overline{E}$ refer to the maximum energy limit of the battery unit.

E_0 refers to the initial energy stored in the battery.

7. Imported power limits

$$\underline{P}_{in} \leq P_{in,j} \leq \overline{P}_{in},\ (j = 1, ..., N) \tag{3.14}$$

$\underline{P}_{in}$ refer to the minimum imported respectively.

$\overline{P}_{in}$ refer to the maximum imported respectively.

For utility applications, the imported power is limited to 15 kW. The minimum imported power is zero kW. For the demand side applications, no limit will be imposed.

8. Integer and binary variables

$$W_{gi,j}, W_{lk,j} \in [0, 1] \tag{3.15}$$

$W_{gi,j}$ refers to a binary variable and takes either 0 or 1 value.

$W_{lk,j}$ refers to a binary variable and takes either 0 or 1 value.

3.3 Demand Side Application: Peak Shaving

In this scenario we assume that the BESS is owned by a community. The main purpose of BESS is peak shaving or to keep the imported power constant. We assume that the community has no other energy sources but it has a BESS and switchable loads. The optimization problem is formulated to minimize the cost of power purchasing and penalize any deviation from the scheduled power. The scheduled power is assumed to be the average load for 24 hours.

3.3.1 Decision Variables

In this optimization problem the vector of the decisions variables is as follows:

$$X = [\cdots P_{in,j}\ \ P_{b,j}\ \ C_b\ \ E_b \cdots]^T \tag{3.16}$$

j	refer to $j-th$ hour and $N = 24$.
$P_{b,j}$	refers to the discharged from or charged to the battery system at the $j-th$ hour.
$P_{in,j}$	refers to the imported power at the $j-th$ hour.
C_b	refers to the rating power of the battery energy system.
E_b	refers to the rating energy of the battery energy system.

3.3.2 Objective Function

The objective function is to minimize the total cost which is the sum of the cost of imported power, and the cost of the BESS and the penalty due to imported power deviation from the scheduled power.

$$\min_{P_{in,j}, C_b, E_b} \sum_{j=1}^{N} \left(\lambda_j P_{in,j} + Penalty(P_{in,j} - P_{sch})^2\right) + \beta_1 C_b + \beta_2 E_b \tag{3.17}$$

P_{sch}	refers to the scheduled power to be purchased by the community.
$Penalty$	refers to the penalty for the deviation from the scheduled power.

3.3.3 Constraints

The optimization problem is subject to the following constraints:

1. Power balance

$$P_{b,j} + P_{in,j} = D_j, \; (j = 1, ..., N) \tag{3.18}$$

2. Power rating limits of battery energy system

$$-C_b \leq P_{b,j} \leq \; C_b \; (j = 1, ..., N) \tag{3.19}$$

3. Energy rating of the battery energy system

$$\underline{E_b} \leq E_0 + \sum_{j=1}^{n} P_{b,j} \leq \overline{E_b}, \; (n = 1, ..., N-1) \tag{3.20}$$

C_b refers to the power rate of the battery energy system.

$\underline{E_b}$ refers to the minimum energy limit of the battery unit.

$\overline{E_b}$ refers to the maximum energy limit of the battery unit.

3.4 Case Studies and Numerical Examples

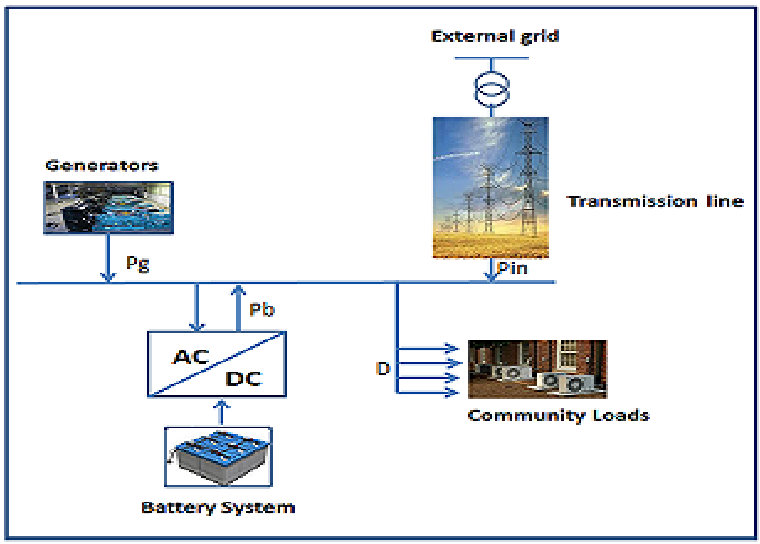

Figure 3.2: The study system for BESS with utility.

3.4.1 BESS Applications in Utility Side

The study system is shown in Fig. 3.2. BESS applications in utility side and demand side are presented in two different cases. To investigate the BESS application in utility side, the utility owns the BESS. The utility also owns generators. In addition, the utility has interconnections with the external grid to have power imported. Dynamic price for the imported power is give (Fig. 3.4). The objective of the utility is to minimize the operating cost and meet the load demands (Fig. 3.3). For the demand side applications, the BESS is owned by the community and the community purchases and imports power from the utility at a dynamic price (Fig. 3.4). The load profile is shown in Fig. 3.3. The community, however, does not own any generators. The proposed MIP model is tested

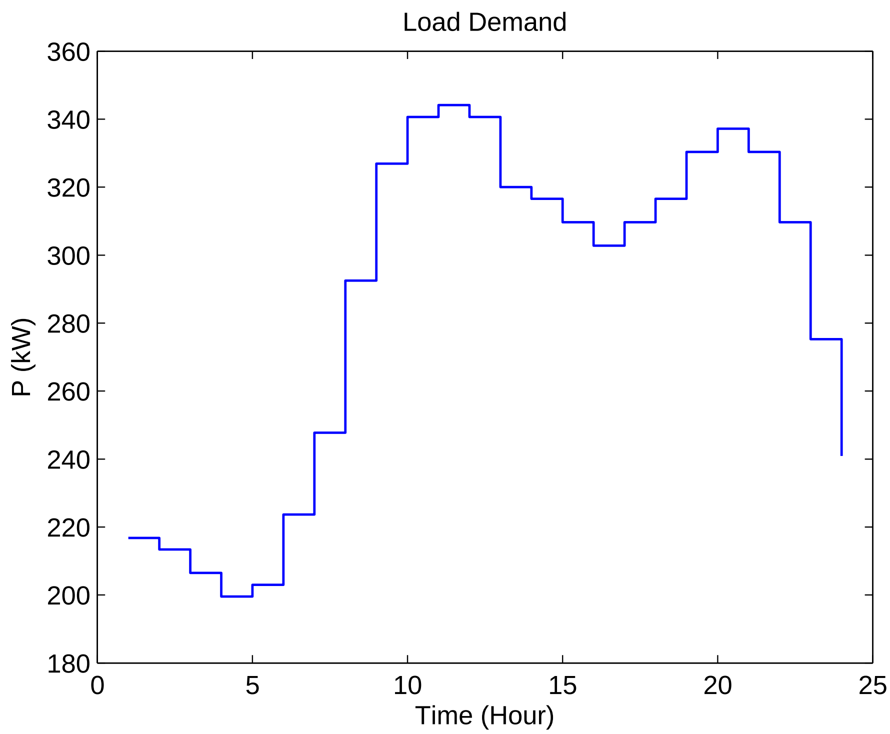

Figure 3.3: Load profile for a day.

using TOMLAB/CPLEX Package. The studied system shown in Fig. 3.2 consists of six generators, a BESS, and load demands with profile shown in Fig. 3.3. Price of the imported power from the external is presented in Fig. 3.4. This price profile is obtained from Ameren Corporation website [61] for a winter day. The specifications of the generators are presented in Table 3.1 and Table 3.2. Fuel cost of the generators are calculated using following equation:

$$F_i = a_i P_i^2 + b_i P_i + c_i. \tag{3.21}$$

In this case, firstly we present the base scenario where no switchable loads are presented. Then, two scenarios are considered to investigate the impact of the switchable loads on the BESS. In the first scenario, penalty is imposed on switching off any switchable load without considering any other constraints. In the second scenario, constraints are imposed on switchable loads: (i) any switchable

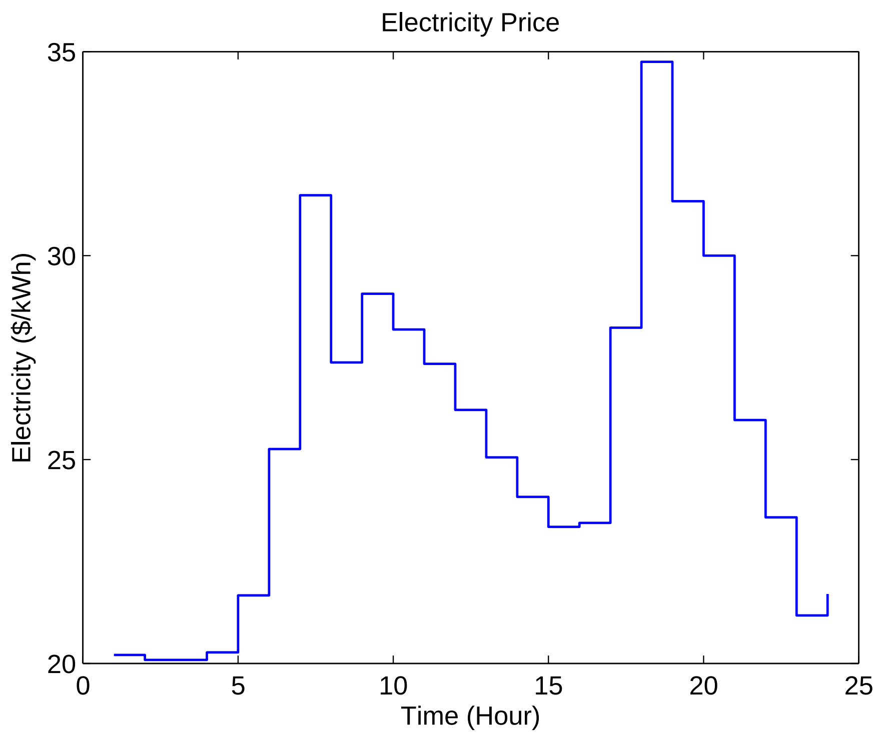

Figure 3.4: Electricity price for a day.

load must run for at least 19 hours each day; (ii) Once the switchable load is on, it must continue being on for 6 hours consecutively. We assume that each switchable load is represented by 3 kW. Therefore, the following constraints must be added to the model:

$$\sum_{n=j}^{j+DT_k-1} [1 - V_{k,n}] \geq DT_k[V_{k,j-1} - V_{k,j}], (j = 1, ..., N) \tag{3.22}$$

DT_k refers to minimum up time of the $k - th$ switchable load.

$$\sum_{j=0}^{j=24} [1 - V_{k,j}] \geq M_{on}, (k = 1, ..., N_s) \tag{3.23}$$

M_{on} refers to the minimum number of hours which any switchable load should be on.

Table 3.1: Specifications of the generators I

Unit	a_i $\left(\frac{\$}{kW^2h}\right)$	b_i $\left(\frac{\$}{kWh}\right)$	c_i $\left(\frac{\$}{h}\right)$	$\underline{P}_i$ (kW)	$\overline{P}_i$ (kW)
1	0.01433	27.8893	118.8206	5	20
2	0.01261	24.6637	118.1083	5	20
3	0.00812	18.1000	218.3350	5	50
4	0.00463	10.6940	142.7348	30	70
5	0.00143	10.6616	176.0575	50	100
6	0.00199	7.6121	313.9102	30	120

Table 3.2: Specifications of the generators II

Unit	UT (h)	DT (h)	SU (kW)	SD (kW)	RU (kW)	RD (kW)
1	8	6	5	10	5	5
2	8	6	5	10	5	5
3	8	6	10	15	5	10
4	8	6	20	15	10	10
5	8	6	30	20	15	15
6	8	6	30	20	20	20

3.4.1.1 Simulation Results

The three scenarios are compared.

- Base scenario without switchable loads
- With switchable loads and imposed penalty. Five switchable loads are considered.
- With switchable loads, imposed penalty and switchable load constraints. Five switchable loads are considered.

Fig. 3.5 shows the optimal dispatch of each generator for the three scenarios. While three generators are not committed, it can be seen that all of the other three generators are committed to dispatch their maximum limits at the time of the peak loads. Fig. 3.6 and Fig. 3.7 present the battery power dispatch level and energy level for 24 hours. Positive power means the battery is discharging while negative power means charging. Comparing the price and load profiles, we can find that during light load and low price periods, the BESS will get charged while during peak load and high price

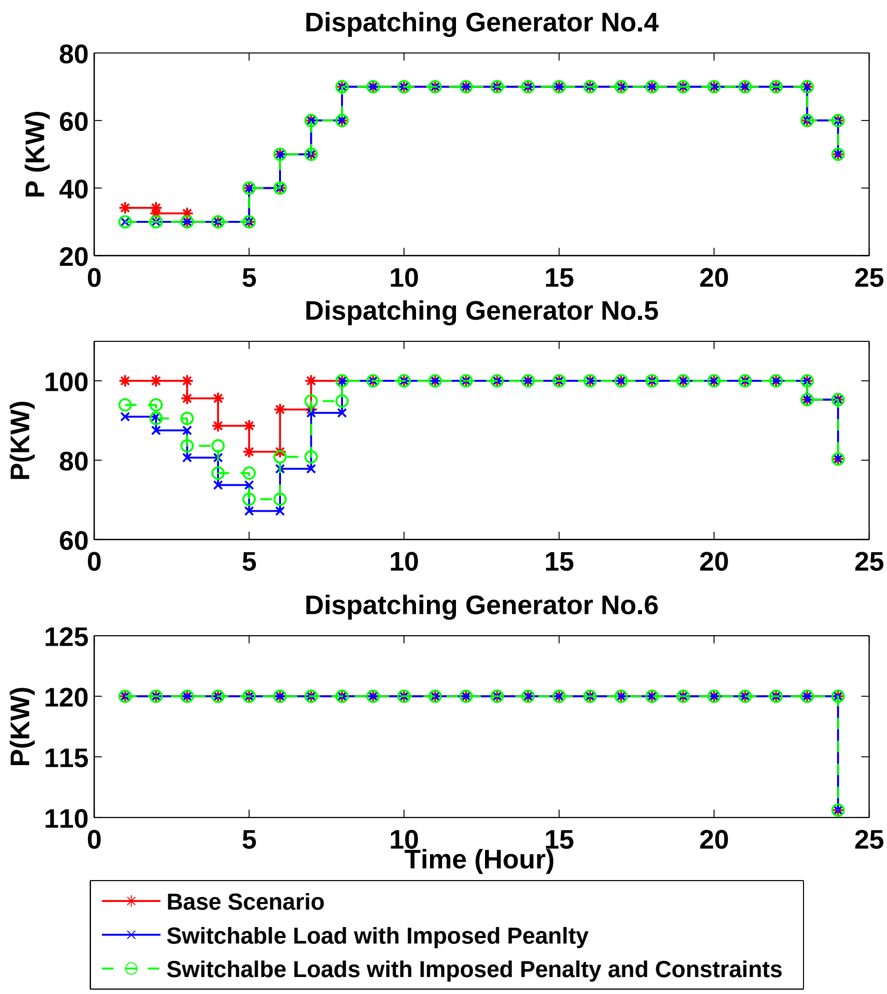

Figure 3.5: Generator dispatch level; five switchable loads are considered; penalty of switching off: \$1 for 3 kW.

periods, the BESS discharges. In addition, with switchable loads, the charge and discharge levels of the BESS are less than those without switchable loads. In turn, the energy capacity required for the BESS is much less. Therefore, presence of switchable loads reduces the size of the battery.

Comparing the case of five switchable loads and ten switchable loads, we can find that with higher penetration of switchable loads, the size of BESS will be reduced even more.

When the constraints for switchable loads are imposed, the requirement for battery power and energy size will go slightly up. In terms of optimization problem, imposing additional constraints is equivalent to reducing the feasible region. Therefore, for minimization problem, the cost will go up. This additional cost is also manifested in the requirement of increasing battery size. Fig. 3.8 and Fig. 3.9 show the impact of the switchable loads on the load profile. Both figures demonstrate that switchable loads are effective to shave peak demand. Fig. 3.9 shows that the higher the penetration of switchable load, the flatter the load profile becomes. Fig. 3.10 presents the switching status of five loads. It can be observed that without the minimum on time constraints, there is more flexibility for switchable loads and more loads are switched off during Hour 20 when the demand is at its second peak. With the minimum on time constraint imposed, at Hour 20, there are less loads switched off. Table 3.3 shows the results of different scenarios to investigate the impact of the switchable loads. It can be found that increasing the number of switchable loads can help reduce the size the BESS. For example, with five switchable loads, the energy size and the power size can be reduced by 1/3. With more switchable loads, we see more reduction in size. With constraints imposed, the requirement for the energy size and the power size is higher. It is found that for the

Table 3.3: Summary of BESS applications in the utility side scenarios

Scenario	Ns	C_b kW	E_b kWh
Base	0	39.11	265.130
Penalty Imposed	5	24.161	169.130
Penalty Imposed	10	9.161	64.130
Penalty Imposed	14	3.11	19.130
Constraints Imposed	5	27.161	190.130
Constraints Imposed	10	16.447	115.130
Constraints Imposed	14	7.876	55.130

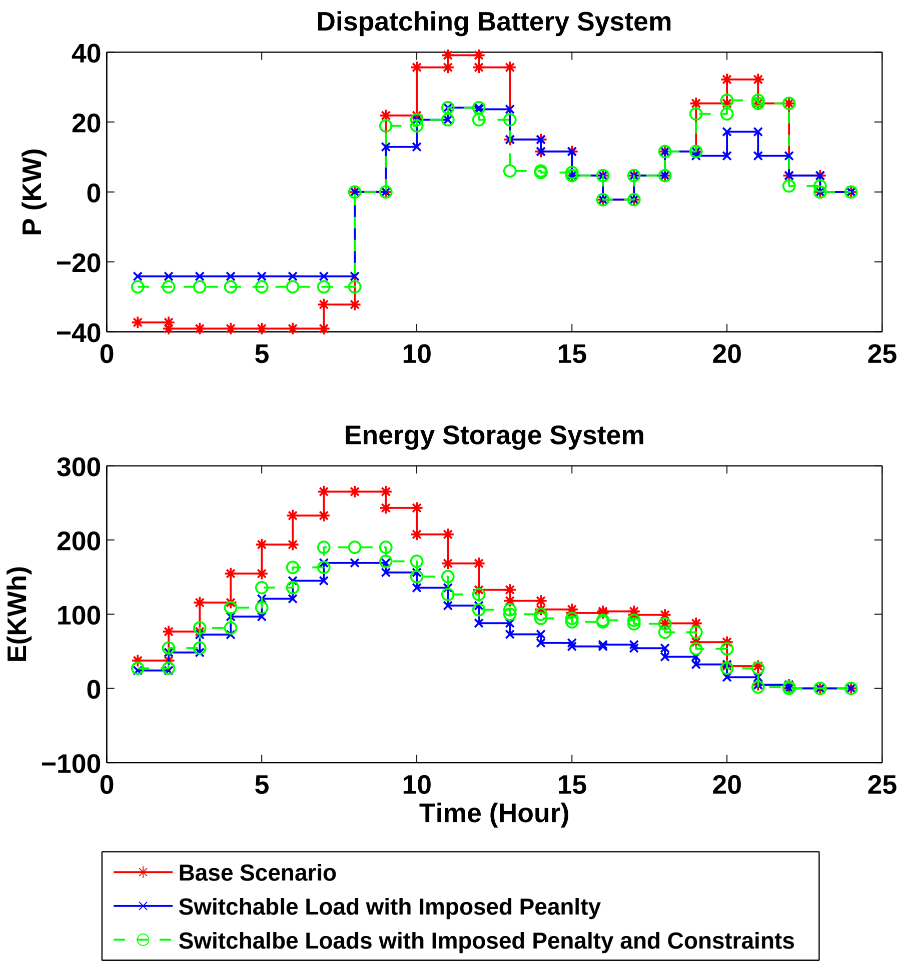

Figure 3.6: BESS power and energy level; five switchable loads are considered; penalty of switching off: \$1 for 3 kW.

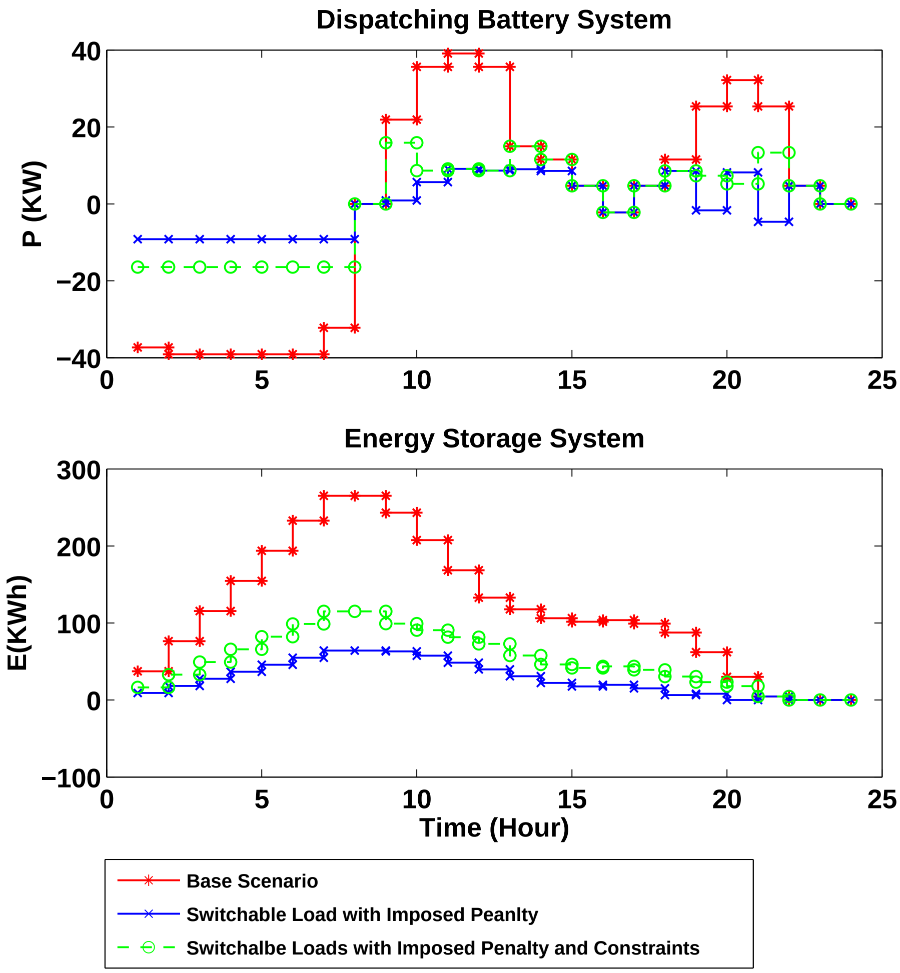

Figure 3.7: BESS power and energy level; ten switchable loads are considered; penalty of switching off: \$1 for 3 kW.

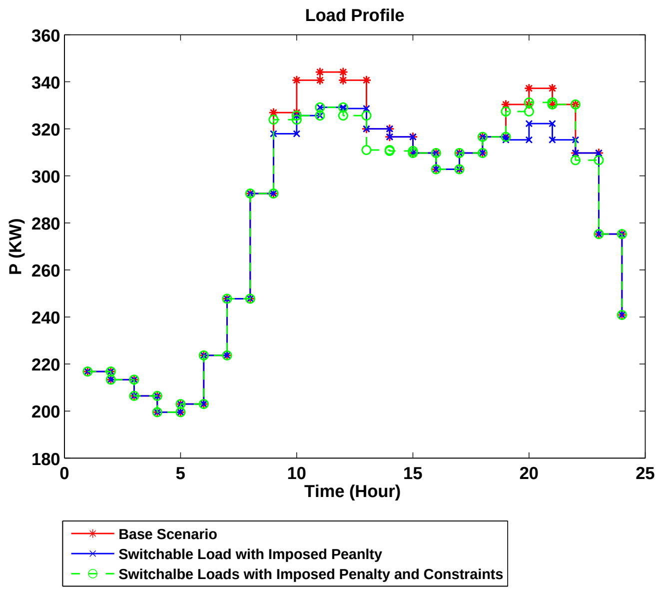

Figure 3.8: Switchable load effect on load profile; five switchable loads are considered.

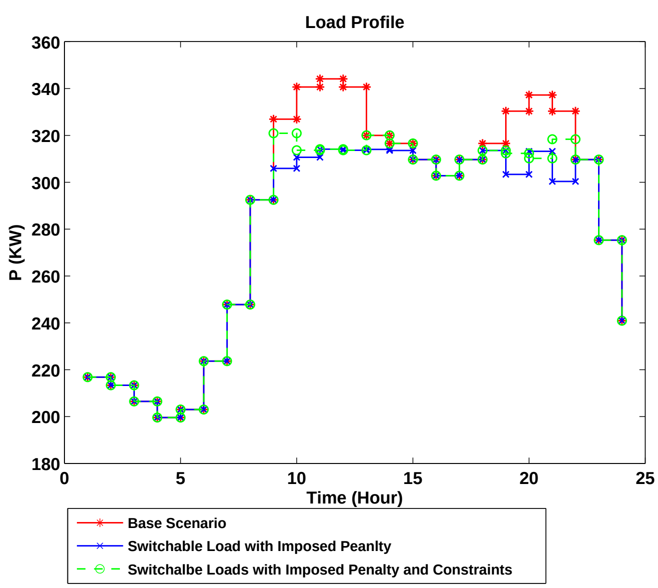

Figure 3.9: Switchable load effect on load profile; ten switchable loads are considered.

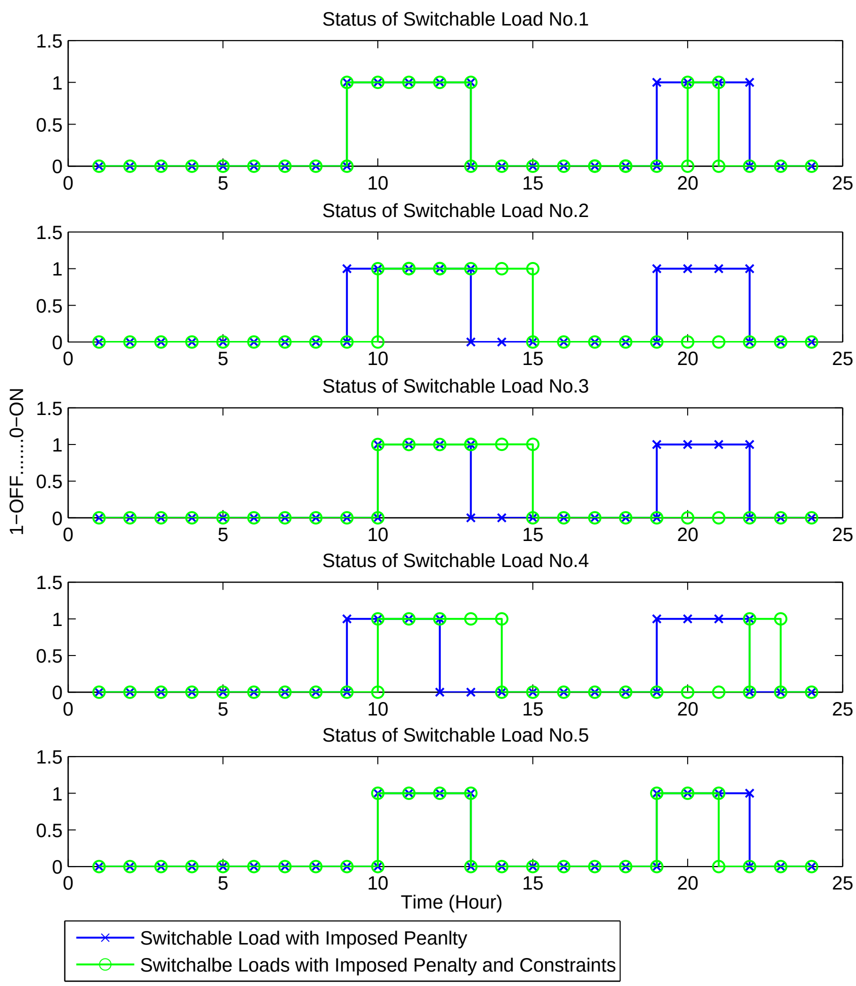

Figure 3.10: Switchable load status; five switchable loads are considered.

system studied, with 5% penetration of switchable loads ($N_s = 5$, each switchable load 3kW), the size of energy storage can be cut down 30%.

3.4.2 BESS Applications in Demand Side

In this application, a community is purchasing power from the utility at dynamic price given in Fig. 3.4 in order to meet its demands shown in Fig. 3.3. The community is requested to schedule a constant power from the grid. A penalty would be imposed on any deviation in the scheduled power. The power schedule is usually the average of the daily demand.

The most conservative size for a battery system can be obtained by investigating the load profile for 24 hours. The BESS is used to compensate the variation of load and the imported power will be kept constant at the average power level. The power size of the BESS is the maximum difference between load and the average load value over 24 hours. The energy size can be found by integrating the power difference over a valley filling period. The computing of power and energy size is demonstrated in the following two equations:

1. Upper Bound on Energy Rating

$$E_{batt} \leq \int_0^{24} (P_{Demand} - P_{ave})dt, \quad P_{Demand} \geq P_{ave} \tag{3.24}$$

2. Maximum value of charging or discharging power

$$C_{batt} = max \left\{ |P_{ave} - P_{Demand}(j)| \right\}, \quad (j = 1, ..., 24) \tag{3.25}$$

The computed battery size is 510 kWh for total storage and 88 kW for charging and discharging power.

For the optimization problem, the community will try to minimize the total cost of purchasing the power, paying penalty and paying battery. Imposing a penalty on the deviation between the scheduled imported power (288 kW) and the purchased power may have an impact on BESS sizing. To investigate that impact the latter two constraints are added to the mathematical model equations

(14)-(18). Different penalties which are \$1, \$10, and \$ 100 have been considered. Table. 3.4 shows the results of testing each of those penalties. Fig. 3.11 and Fig. 3.12 show that the heavier the penalty imposed, the less deviation between the purchased and scheduled power. They also show that the heavier the penalty imposed, the larger the BESS size is required. With a heavy penalty on imported power deviation, the size of the battery will be close to the most conservative case: 510 kWh and 88 kW. The penalized cost is dependent on the deviation of imported power from

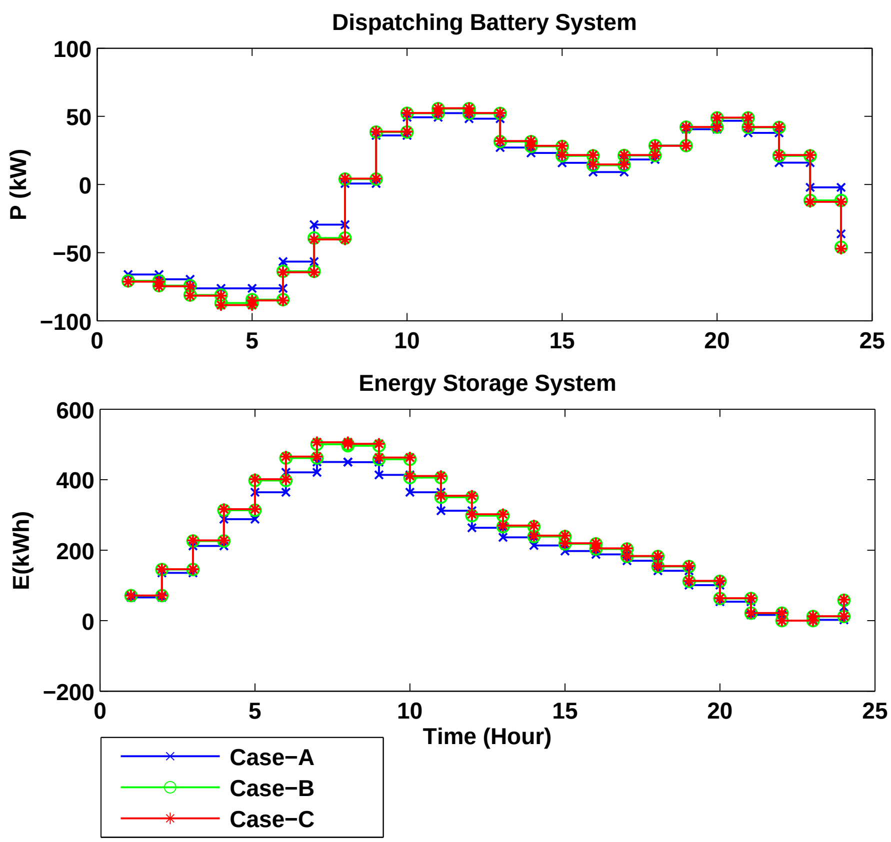

Figure 3.11: BESS power and energy level in demand side applications.

the scheduled power. When the penalty is set to \$1, the maximum power deviation observed from Fig. 3.12 is 4%. The size of the battery is reduced about 10%.

At \$10 penalty rate, the imported power is already very close to the scheduled power and the deviation is insignificant. At \$100 penalty rate, the deviation is also insignificant. Therefore, the related component on power deviation in the objective function has negligible effect on the total

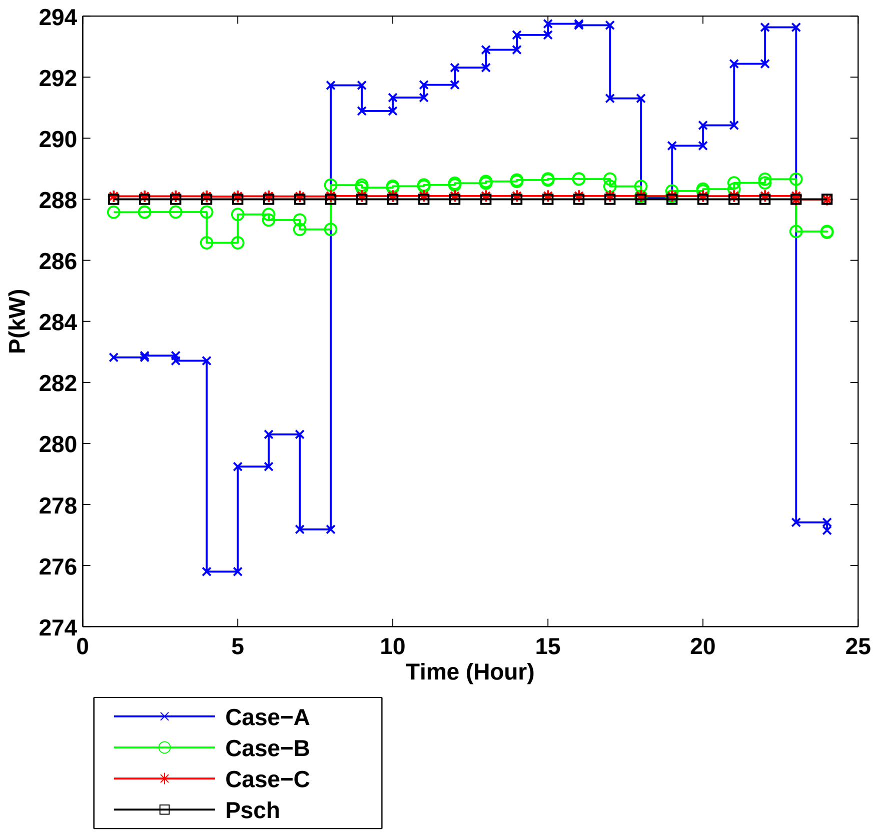

Figure 3.12: Purchased power versus the scheduled power in demand side applications.

Table 3.4: Summary of BESS applications in the demand side scenarios

Scenario	Penalty Cost \$	C_b kW	E_b kWh	$Min.P_{in}$ kW	$Max.P_{in}t$ kW
Case A	1	76.239	450.295	275.79	293.74
Case B	10	87.010	500.51	286.56	288.6
Case C	100	88.526	506.034	287.98	288.1

objective function when the penalty rate increases from \$10 to \$100. This makes the battery power size and energy size remain almost the same for \$10 and \$100 penalty.

3.5 Conclusion

This chapter presents MIP problem formulation to find the size of a BESS. The BESS could be owned by a utility to reduce the operation cost or owned by a community for peak shaving. Switchable loads are considered in the problem formulation and unit commitment is also considered. Objective functions, linear constraints for BESS and switchable load constraints suitable for MIP solving are defined. The optimization problems are solved by commercial tool CPLEX. Case study results demonstrate the impact of switchable load penetration on BESS size. It is found that for the system studied, with 5% penetration of switchable loads, the size of energy storage can be cut down 30%. In addition, the size of the energy storage can also be determined based on multiobjective optimization of imported power deviation and battery cost. If we can tolerate 4% power deviation, we can cut down the size of a BESS by 10%.

CHAPTER 4

HVAC AND ENERGY STORAGE SYSTEMS

4.1 Introduction

A mixed integer programming (MIP) based operation is proposed in this chapter[1] for residential Heating Ventilation and Air-Conditioning Systems (HVAC). The objective is to minimize the total cost of the HVAC energy consumption under varying electricity prices. A simplified model of a space cooling system considering thermal dynamics is adopted. The optimization problems consider 24 hour operation of HVAC. Comfort/cost trade-off is modeled by introducing a binary variable. The big-M technique is adopted to obtain linear constraints while considering this binary variable. The MIP problems are solved by CPLEX. Simulation results demonstrate the effectiveness of HVAC's ability to respond to varying electricity price.

Recently, the implementation and development of a Smart Grid [62] has been increasingly growing and moving toward this technology will bring about notable modifications to the existing power grids at all its levels. The modifications will mostly occur in transmission and distribution grids in terms technology and the way those networks will be operated. Utilities and customers will have chances play an important role in the control of the grid. From utilities sides, they would use advanced technologies such as smart meters, phasor measurement units, developed communication tools, demand response program to implement load management techniques to shave peaks or to shift loads from peak hours to off-peak hours. By accomplishing that, they aim to increase the grid reliability and security. From consumers side, they will be encouraged to get chances from participation in the demand response programs. They can receive money by participating in incentives demand response programs where they are encouraged by utilities to switch off the

[1]This chapter was published in Power Energy Society General Meeting, 2015 IEEE, July 2015, pp. 15. Permission is included in Appendix B.

loads during the peak hours. They can reduce their usage bills by participating price based demand response programs where the utilities implement a dynamic energy pricing mechanism to be high during the peak hours and low during the off-peak hours.

Electricity service providers consider emand response (DR) and Demand Side Management (DSM) programs to better manage the electricity usage patterns of customers [63, 64, 6, 65, 66]. The DR and DMS systems are applied in many cases, especially when the demand for power is more than the generated power . The biggest percentage of electrical loads of most commercial facilities, such as large office buildings, hotels, etc. is comprised of the lighting and HVACs [67, 68, 69, 7] .The U.S. Department of Energy estimates that HVAC loads account for 40% - 60% of the energy consumption in U.S. commercial and residential buildings [70]. The power consumed by HAVC loads can be controlled manually by the customers or automatically by the appliances.

Regarding HVAC optimal operation models, several models have been developed to determine the potential benefits when implementing the DSM and DR strategies. Authors in [27] proposed an analysis for demand response that considers modeling loads as single components rather than lump model. They argued that when considering loads as single components, this would give more realistic operation for some complex components which have so complicated operational constraints. Therefore, the authors developed a dynamical model for HVAC loads based on simulations and performance tests on an actual unit. The HVAC parameters are collected based on historical data. Those models are used to investigate the impacts that HVAC loads can provide to DSM programs. Authors in [28] proposed an algorithm that can help demand response programs aggregators automatically schedule the energy consumed by thermostatically controlled loads and make better decisions to dispatch their events. The authors used Karush Kuhn Tucker (KKT) conditions to model the optimization problem. Here, the authors didnt consider practical operating constraints when modeling HVAC models. This study didnt investigate the impacts of the optimal scheduling on the demand response or on the consumers comfort settings. In [29], the authors have investigated a design of a residential HVAC system whose objective function is to respond to energy received from the utility to determine an optimal plan for trading off between comfort and cost. They used a stochastic dynamic programming to develop an HVAC control strategy where it can permit the controller to make the best decision responding to varying power prices. Then, the thermal dynamics of the HVAC system and the house were represented and simulated using physics-based models to be more practical for the system control purposes of the residential HVAC system. Finally, the economic effects of this trade-off formulation were investigated to explore their feasibility. In [30], the possibility that aggregating a large number of HVAC loads can provide intra-hour load balancing services was investigated using a direct load control algorithm. In [31], a linear-sequential-optimization- enhanced, multiloop algorithm was proposed to solve the appliance commitment problem concerning the thermostatically controlled household loads. Electric water heater was modeld to simulate those loads. In [32],the authors investigated the efficiency of a hybrid system combining renewable energy source and battery system to power a controllable HVAC load. They used a genetic algorithm approach to minimize the cost and increase the efficiency.

This work will investigate the effects that the optimal scheduling of HVAC operation with and withouth BESS can have when considering demand response applications. Different models are investigated in this chapter. First, when the HVAC is adjusted to respond to the varying price and satisfying all comfort settings. Second, when the HVAC is adjusted to provide optimal comfort/cost trade-offs for the resident based on the varying prices of the energy. Third, when a BESS is installed and can supply the HVAC with power. HVAC on/off states, BESS states will be determined for a 24-hour period for each case where it applies.

4.2 Thermal Dynamics Models of an HVAC Unit

Equivalent Thermal Parameters model of a residential HVAC is shown below: where:

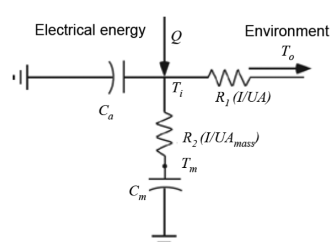

Figure 4.1: The study system of thermal model.

Q	refers to heat rate for HVAC unit (Btu/hr or W).
UA	refers to standby heat loss coefficient (Btu/^{o}F.hr or $W/^o$C).
R_1	refers to 1/UA.
R_2	refers to $1/UA_{mass}$.
T_o	refers to ambient temperature (^{o}F or^{o}C).
T_i	refers to air temperature inside the house (^{o}F or ^{o}C).
T_m	refers to mass temperature inside the house (^{o}F or ^{o}C).
C_a	refers to air heat capacity (Btu/^{o}F or $J/^o$C).
C_m	refers to mass heat capacity (Btu/^{o}F or $J/^o$C).

A state space description of the ETP model is

$$\dot{x} = Ax + Bu \tag{4.1}$$

$$y = Cx + Du \tag{4.2}$$

$$\dot{x} = \begin{bmatrix} \dot{T_i} \\ \dot{T_m} \end{bmatrix} \tag{4.3}$$

$$x = \begin{bmatrix} T_i \\ T_m \end{bmatrix} \tag{4.4}$$

$$A = \begin{bmatrix} -(\frac{1}{R_2C_a} + \frac{1}{R_1C_a}) & \frac{1}{R_2C_a} \\ \frac{1}{R_2C_m} & -(\frac{1}{R_2C_m}) \end{bmatrix},$$
$$B = \begin{bmatrix} \frac{T_0}{R_1C_a} + \frac{Q}{C_a} \\ 0 \end{bmatrix}, \; C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \; D = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

A simplified model used in [30] of the space cooling unit is described as following. The temperature of the room can be calculated when the status of the HVAC is OFF as following

$$T_{room}^{t+1} = T_o^{t+1} - (T_o^{t+1} - T_{room}^t) * e^{-\Delta t/RC} \tag{4.5}$$

The temperature of the room can be calculated when the status of the HVAC is ON as following

$$T^{t+1}_{room} = T^{t+1}_{o} + QR - (T^{t+1}_{o} + QR - T^{t}_{room}) * e^{-\Delta t/RC} \tag{4.6}$$

T_{room}	refers to room temperature (^{o}F or ^{o}C).
C	refers to equivalent heat capacity (Btu/^{o}F).
R	refers to equivalent thermal resistance (^{o}C/W).
Q	refers to equivalent heat rate (W).
t	refers to air temperature inside the house (minute).
Δt	refers time step (1 minute).

4.3 Optimization Models of HVAC Applications

Different situations are considered to investigate the applications of the HVAC for the optimal demand response. For computational tractability, the planning horizon of the house resident is discretized into time periods n= 1,....,N, and the continuous thermal dynamics of the house are correspondingly discretized. Three models are developed in this chapter.

4.3.1 HVAC Responding to a Varying Price

The optimization model here is developed based on the assumption that the HVAC is adjusted to respond to varying energy prices and to satisfy all comfort and thermal settings.

4.3.1.1 Decision Variables

The decision variables for the optimization problem are listed as follows:

$$X = [\cdots P_{in,j} \;\; W^{k}_{j} \cdots] \tag{4.7}$$

j refers to jth period.

k refers to kth No. of HVAC unit.

$P_{in,j}$ refers to purchased power at the jth period.

W_j^k refers to a binary variable that is equal to 1 if the HVAC kth is on at the jth period and 0 otherwise.

4.3.1.2 Objective Function

$$\min_{W_j^k} \sum_{j=1}^{N} \lambda_j P_{in,j} \tag{4.8}$$

λ_j refers to the energy price at the jth period.

4.3.1.3 Constraints

- Thermal Constraints

$$T_{room}^{j+1} = T_o^{j+1} + W_j^k * QR - (T_o^{j+1} + W_j * QR - T_{room}^j) * e^{-\Delta t/RC} \tag{4.9}$$

$$T_{min} \leq T_{room}^{j+1} \leq T_{max} \tag{4.10}$$

T_{min} refers to the minimum setpoint of the HVAC thermostat.

T_{max} refers to the maximum setpoint of the HVAC thermostat.

- Power Balance Constraints

$$P_{in,j} = \sum_{i=1}^{k} W_j^k * P_{a/c}^k \tag{4.11}$$

$$P_{min} \leq P_{in,j} \leq P_{max} \tag{4.12}$$

P_{min} refers to the minimum limit purchased power.

P_{max} refers to the maximum limit purchased power.

$P_{a/c}$ refers to the rated power of the HVAC unit.

4.3.2 Comfort/Cost Trade-Offs

The optimization model here is developed based on the assumption that the HVAC is adjusted to provide optimal comfort/cost trade-offs for the resident based on varying prices of the energy. The resident would define a desired pirce that he would allow to increase the maximum setpoint of the thermostat in case the energy price is greater than his desired price.

4.3.2.1 Decision Variables

$$X = [\cdots P_{in,j} \;\; W_j^k \;\; W_\alpha^k \cdots] \tag{4.13}$$

W_α^k refers to a binary variable that is equal to 1 if the energy price is greater than the desired price and 0 otherwise.

$$W_\alpha^k = \begin{cases} 1, & \lambda_{desired} \leq \lambda_j \\ 0, & \text{elsewhere} \end{cases}$$

$\lambda_{desired}$ refers to the desired price which can be paid to purchase power.

4.3.2.2 Objective Function

$$\min_{W_j^k} \sum_{j=1}^{N} \lambda_j P_{in,j} \tag{4.14}$$

4.3.2.3 Constraints

$$\lambda_{desired} - \lambda_j + M * W_\alpha^k \geq 0 \tag{4.15}$$

$$\lambda_{desired} - \lambda_j - M * (1 - W_\alpha^k) < 0 \tag{4.16}$$

M referes to a big number.

- Thermal Constraints

$$\begin{aligned} T_{room}^{j+1} =& T_o^{j+1} + W_j^k * QR - (T_o^{j+1} \\ &+ W_j * QR - T_{room}^{j}) * e^{-\Delta t/RC} \end{aligned} \tag{4.17}$$

$$T_{min} \leq T_{room}^{j+1} \leq T_{max} + W_\alpha^k * T_\alpha \tag{4.18}$$

T_α refers to the allowed incremental in the temperature when the energy price is greater than the desired price.

- Power Balance Constraints

$$P_{in,j} = \sum_{i=1}^{k} W_j^k * P_{a/c}^k \tag{4.19}$$

$$P_{min} \leq P_{in,j} \leq P_{max} \tag{4.20}$$

4.3.3 Battery and HVAC Applications in Demand Response

The optimization model here is developed based on the assumption that there is a BESS which is installed and can be charged and store the energy from the grid, and can be discharged and supply the HVAC with power.

4.3.3.1 Decision Variables

$$X = [P_{in,j} \;\; P_{b,j} \;\; W_j^k] \tag{4.21}$$

$P_{b,j}$ refers to the Battery power at jth period.

4.3.3.2 Objective Function

$$\min_{W_j^k, P_{b,j}} \sum_{j=1}^{N} \lambda_j P_{in,j} \tag{4.22}$$

4.3.3.3 Constraints

- Thermal Constraints

$$
\begin{aligned}
T_{room}^{j+1} = & T_o^{j+1} + W_j^k * QR - (T_o^{j+1} \\
& + W_j * QR - T_{room}^j) * e^{-\Delta t/RC}
\end{aligned}
\tag{4.23}
$$

$$T_{min} \leq T_{room}^{j+1} \leq T_{max} \tag{4.24}$$

- Power Balance Constraints

$$P_{in,j} = \sum_{i=1}^{k} W_j^k * P_{a/c}^k + P_{b,j} \tag{4.25}$$

$$P_{min} \leq P_{in,j} \leq P_{max} \tag{4.26}$$

- Battery Constraints

  Power rating limits of battery energy system

$$-C_b \leq P_{b,j} \leq \ C_b \tag{4.27}$$

  Energy rating of the battery energy system

$$\underline{E_b} \leq E_0 + \sum_{j=1}^{n} P_{b,j} \leq \overline{E_b}, \tag{4.28}$$

C_b refers to the power rate of the battery energy system.

E_b refers to the energy rate of the battery energy system.

$\underline{E_b}$ refers to the minimum energy limit of the battery unit.

$\overline{E_b}$ refers to the maximum energy limit of the battery unit.

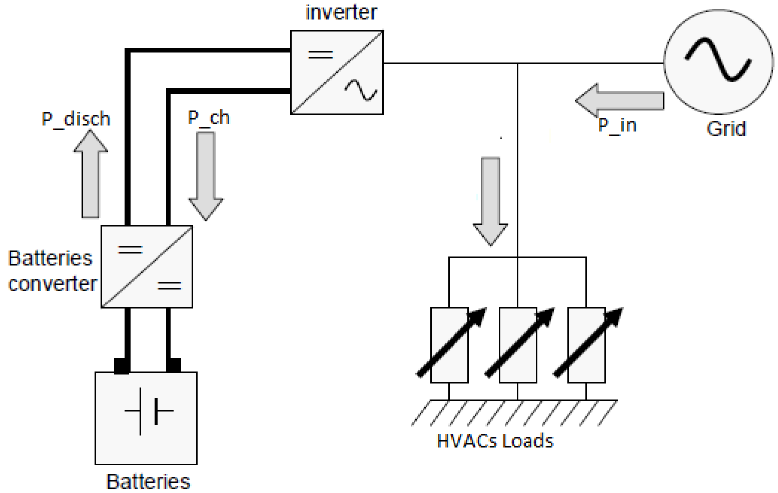

Figure 4.2: The study system of HVAC with power grid.

Table 4.1: Parameter values for HVAC

	$Q(W)$	$R(F/W)$	$C(J/F)$
Values	400	0.1208	3599.3

4.4 Case Studies and Numerical Examples

4.4.1 The Study System

The study system shown in Fig. 4.2 consists of six HVAC units (rated at 5 kW) in their cooling modes. HVAC units consume electricity from the grid at a varying price, shown in Fig. 4.3, during known periods. Rooms temperature should be maintained within a defined range by the consumer. Here, the consumer is to set thermostat point settings to 71 F as minimum limit and 75 F as maximum limit. The ambient temperature is shown in Fig. 4.4. The parameters C , R,and Q which have been introduced in the above thermal model are shown in Table. 5.1. A BESS will be added later to investigate its effects on HVAC applications for demand response. The base study shown in Fig. 4.4 is to operate the HVACs to satisfy the thermal constraints comfortably and normally without responding to the energy signal price.

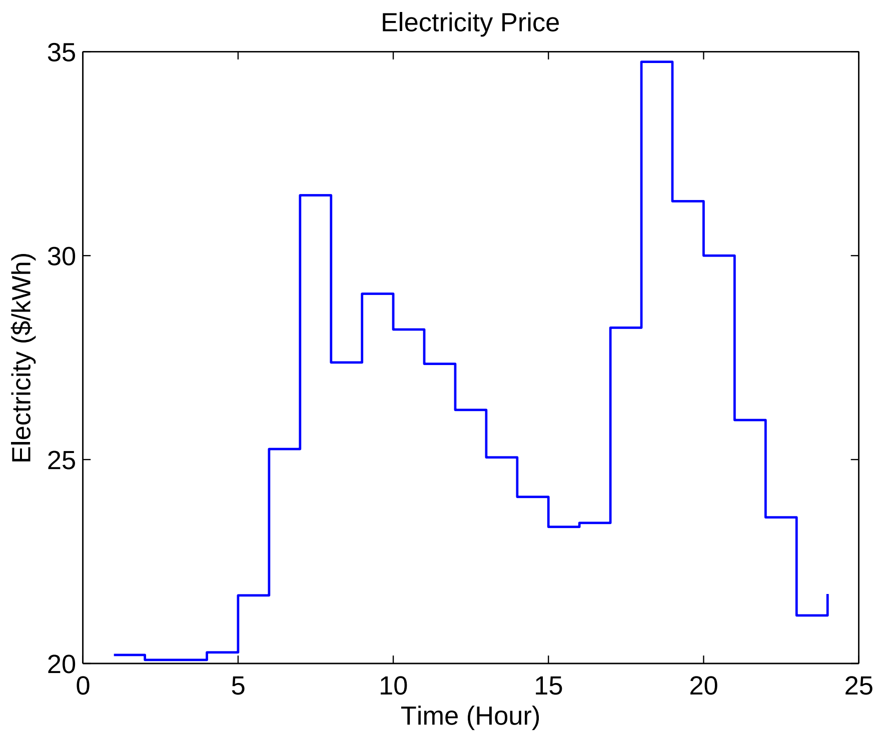

Figure 4.3: Energy price.

4.4.2 HVAC Responding to a Varying Price

In this case, which we would call case-A, we consider operating HVACs while taking the price signal in our considerations. In another case, which we would call case-B, we consider operating HVACs while taking the price signal in our considerations and putting limits on the purchased power. These cases are to be compared with the base study. Table. 4.2 shows a comparison between all of the three cases. It can be noticed . The total cost of purchasing the energy is reduced from 18.62 for the base case to 17.74 for the Case-A which represent %4.73 reduction. For the case-B the reduction is %4.5. Fig. 4.5 shows a comparison between the load profile in the base case and the case-A. It can be noticed that the case-A (dotted stairs) have a such behavior to avoid occurring in the peak price periods while the base case (solid stairs) behaves indifferently to the energy price signals. That behavior is called "Load Shifting"' which is one of the popular forms of load management to achieve demand response. Fig. 4.6 shows a comparison between the load profile in the case-A and the case-B. It can be noticed that the case-B (dotted stairs) have

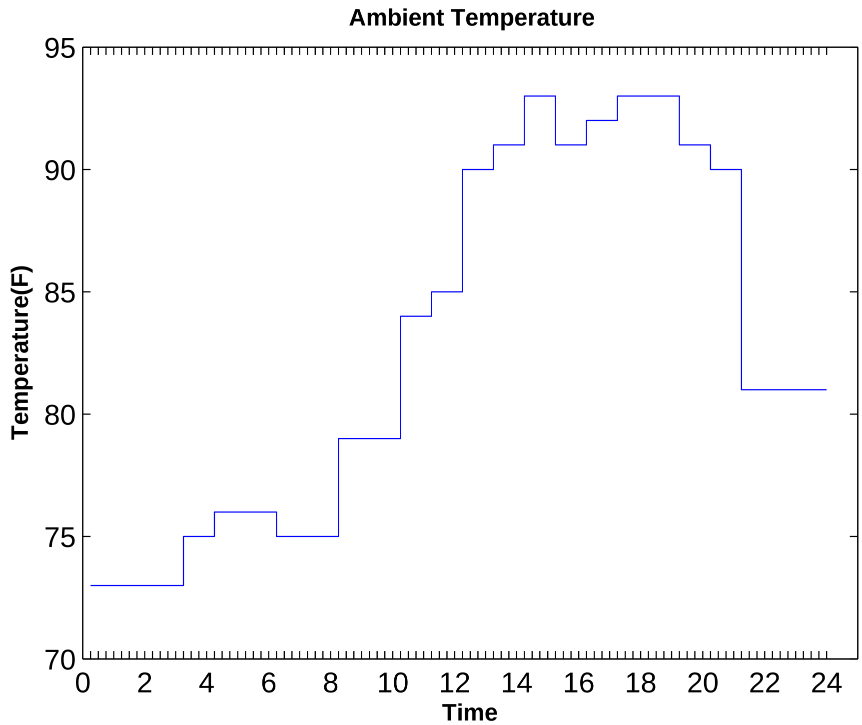

Figure 4.4: Ambient temperature.

not exceeded 15 kW which is the maximum power limit which can be purchased. The peak load which is 25kW in the case-A (solid stairs) is shaved to 15 kW in the (dotted stairs). That behavior is called "Peak Clipping"' which is another popular forms of load management to achieve demand response. All thermal constraints and comfort settings were satisfied while shifting the load in case-A and shaving the peak in case-B.

Table 4.2: HVACs behaviors considering dynamic price

Scenario	$ConsumedEnergy$ kWh	$PeakLoad$ kW	$Cost$ \$
Base	67.5	25	18.619
Case A	67.5	25	17.74
Case B	67.5	15	17.791

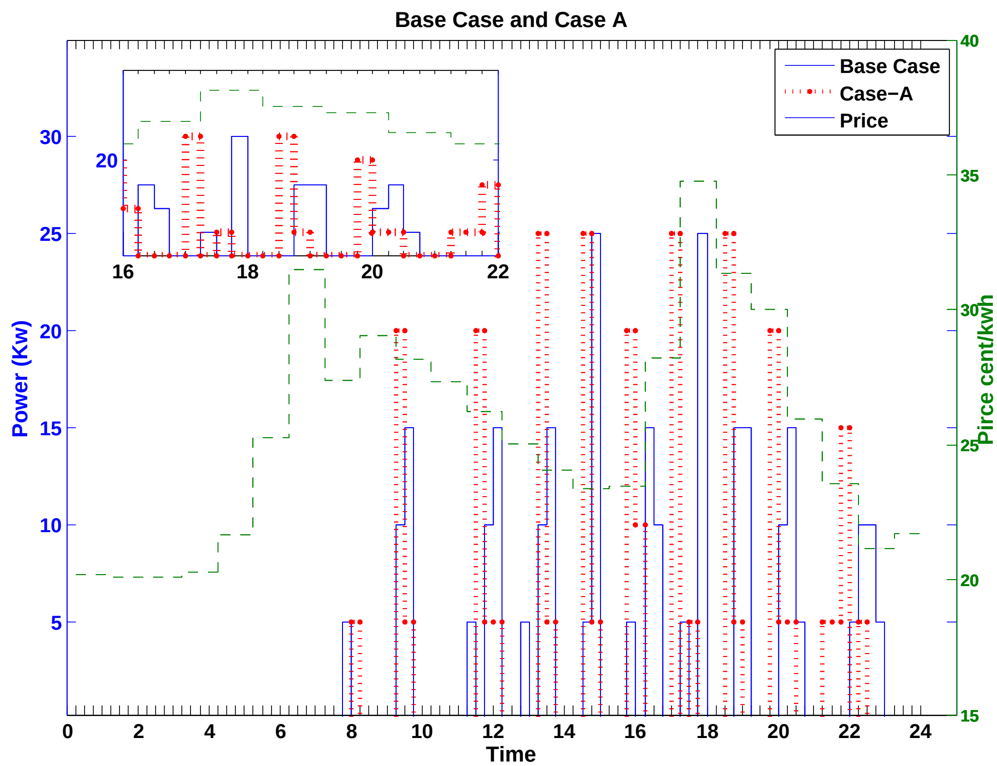

Figure 4.5: Loads profile comparison between the base study and case-A.

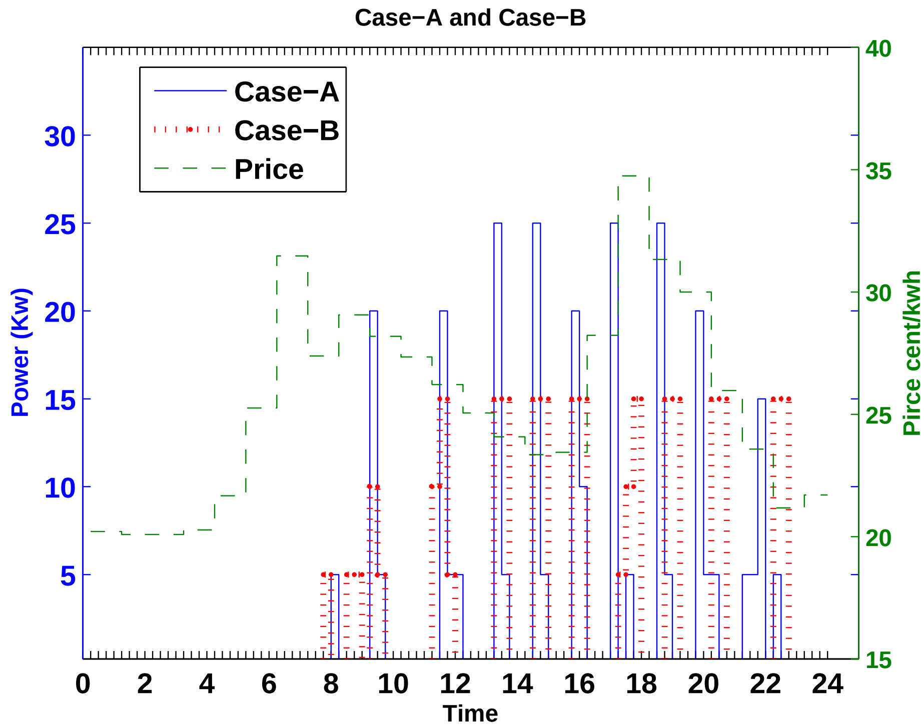

Figure 4.6: Loads profile comparison between case-A and case-B.

4.4.3 Comfort/Cost Trade-Offs

In this case, which we would call case-C, we consider the Comfort/Cost trade-offs for consumers. Here, a maximum desired price of purchasing electricity would be defined. When the energy price exceeds the maximum desired price, the consumer would prefer to allow the maximum temperature setting to increase by a defined quantity. Here we investigate two different scenarios. In case-C1 and case-C2, we set the desired price to be 26 Cent/kWh and assume that we can increase the maximum temperature by 2 degrees and 1 degree for these cases respectively. Changes in the thermostat settings are assumed to be done only on HVAC-1, HVAC-3, and HVAC-5. Fig. 4.7 presents the result of case-C1 and it shows that when the energy price exceeds the desired price, HVAC-1, HVAC-3, and HVAC-5 respond to this increase by changing the thermostat setting of the maximum temperature. Table. 4.4 shows that both energy consumption and total cost are reduced. The cost reduction represent %11.2 in case-C1 and %8.5 in case-C2.

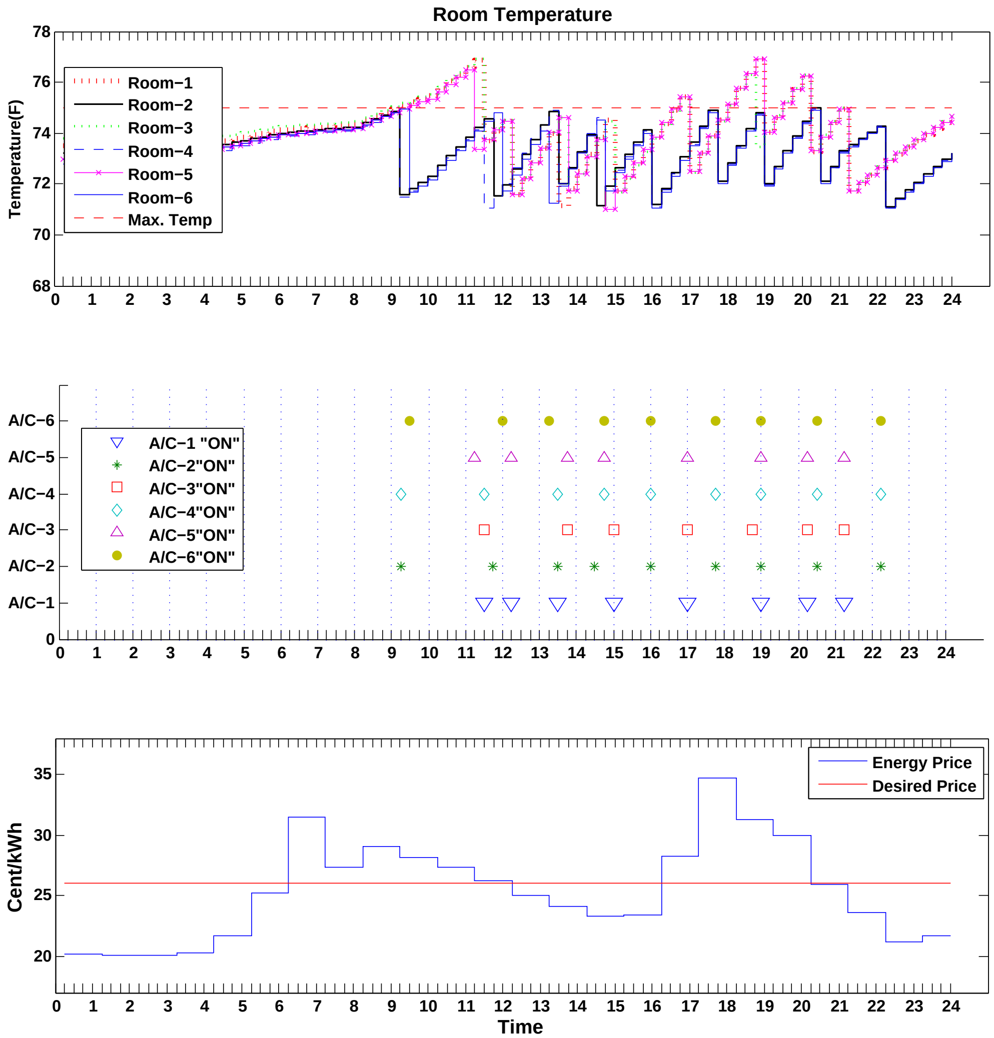

Figure 4.7: HVACs behaviors considering comfort/cost trade-offs case-C1.

Table 4.3: HVACs behaviors considering comfort/cost trade-offs

Scenario	$ConsumedEnergy$ kWh	$PeakLoad$ kW	$Cost$ \$
Base	67.5	25	18.619
Case C-1	63.75	25	16.736
Case C-2	66.25	25	17.050

4.4.4 Battery and HVAC Applications in Demand Response

In this case, which we would call case-D, we consider installing a BESS. Five scenarios are created considering different capacity and energy ratings which are shown in Table. 4.4. In load management, "Valley Filling" is the activity where the system builds load during the off-peak periods. In Fig. 4.8, the solid ellipse shows that during the low price which is normally the off-peak periods, the system is building loads by charging the battery. During the peak time, it can be seen in the dotted ellipse that the battery system is dispatching power to supply HVACs. Cost reduction represented by % 11.3 can be achieved when using BESS with 6 kW and 25 kWh for Capacity and energy ratings respectively.

Table 4.4: HVACs behaviors considering installing BESS

Scenario	$ConsumedEnergy$ kWh	$PeakLoad$ kW	$Cost$ $
Base	67.5	25	18.619
Case D-1 (C_b=3 kW, E=10 kWh)	67.5	25	17.426
Case D-2 (C_b=6 kW, E=10 kWh)	67.5	21	17.385
Case D-3 (C_b=3 kW, E=20 kWh)	67.5	20	17.065
Case D-4 (C_b=6 kW, E=20 kWh)	67.5	30	16.968
Case D-5 (C_b=6 kW, E=25 kWh)	67.5	34	16.718

4.5 Conclusion

The Smart Grid is emerging, and buildings of the future will need Smart Consumption technologies to fully realize its benefits. In this chapter, models are proposed which can help end users' to participate in decision making to better manage their energy consumption in an efficient way. That would increase their participation to achieve an effective demand response which is one of the main goals of Smart Grid. The results of installing a BESS has shown that such approach can provide a different alternative which allows costumers to minimize the total cost of their energy consumption. Different form of load management are demonstrated as the HVACs show potentiality to be a great tool for load management purposes while they are still capable to satisfy all of thermal and other constraints.

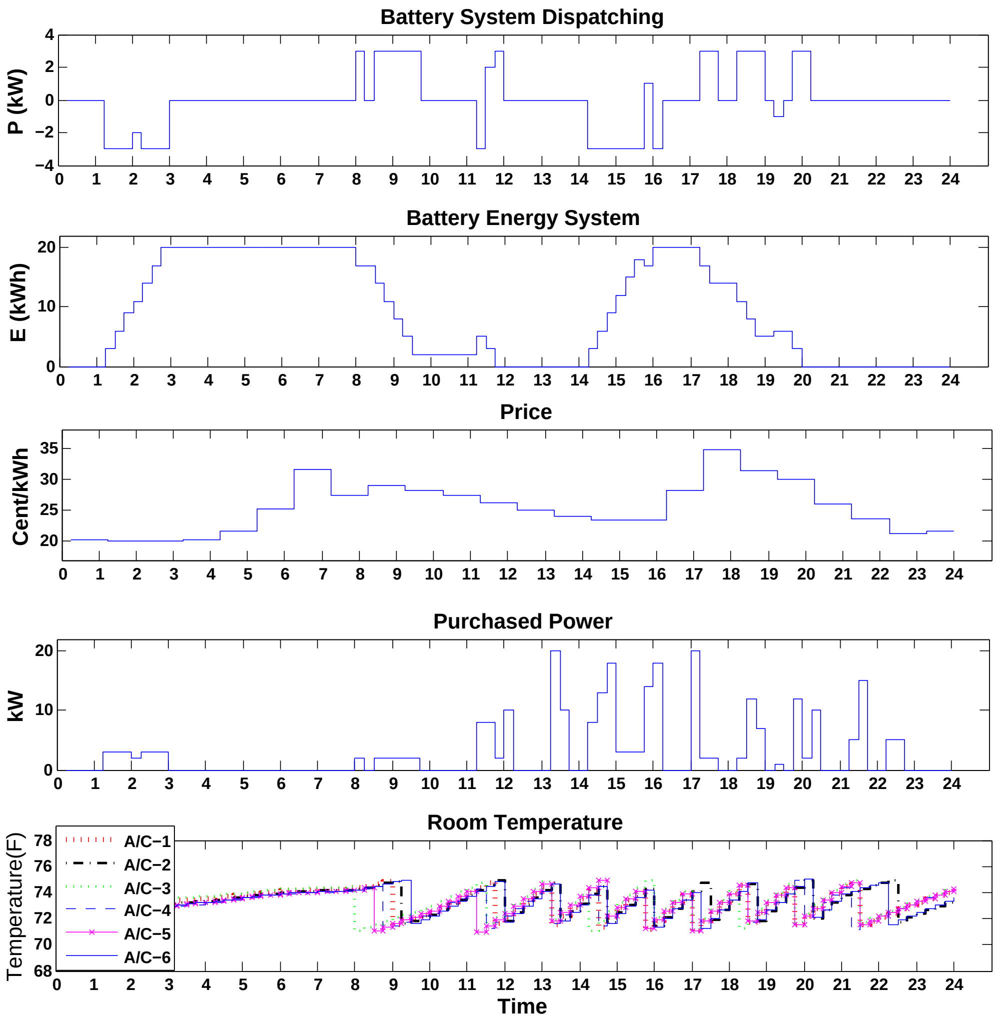

Figure 4.8: HVACs behaviors considering installing BESS case-D3.

CHAPTER 5

SMART BUILDING/ PLANNING WITH UNCERTAIN PV ENERGY

5.1 Introduction

DSM that can provide fast peak shaving and valley filling is receiving more attention than ever. A feature of smart building is to be able to realize DSM. The main load component of a building is heating, ventilation and air-conditioning (HVAC) units. In most places, peak loads occur during the day with high temperature. HVAC loads account for a large portion of the peak loads that could reach to 40% - 60% of the loads in commercial and residential buildings [70].

During the day time, there is much of unexploited solar energy that could be utilized to enhance DSM functions. Therefore, it is essential to use Photovoltaic cells (PV) to harvest the sun energy and convert it to electricity that can power the HVAC units. Consumers can participate in demand response programs that utilities design to move their HVAC loads or part of it from the peak loads hours to the off-peak hours. The utilities provide the consumers with economic incentives and can postpone their needs for building power generation plants, transmission and distribution networks. One example is the cool share program designed by NVEnegrys which give them control over 145 MW of their consumers HVACs loads [71].

It is a great idea to develop and implement a model that can reduce and mitigate the mismatch renewable energy source and controllable HVAC loads. However, the stochastic nature of PV output uncertainty makes it harder to integrate the operation and planning purposes. Therefore, a battery system that can be combined with the renewable energy source and power HVACs loads and mitigate this mismatch. An HVAC system's control inputs include input air pressure and temperature setting. Sophisticated dynamic models with air pressure and temperature setting as the inputs have been adopted in thermal energy storage studies [72, 73]. In electric power planning and operation studies, a simplified thermal dynamic model of first-order is usually adopted, e.g., [31, 74, 75], where the HVAC control input is simplified as on/off status. The on/off status is determined simply by a price comparison rule in [31] while in [74, 75], MIP problems are solved by heuristic methods.

Addressing the issues of uncertainty of renewable energy has been studied in the literature, e.g., [33, 34, 35, 36]. In the aforementioned papers, optimal design and operation of wind/solar hybrid systems is discussed. In [32], the authors investigated the feasibility of meeting controllable HVAC loads by a hybrid energy system combining renewable energy sources and battery energy system. This study didnt consider on/off status. To address uncertainty, stochastic programming problems are usually formulated where numerous scenarios with probability are created. This results in large-scale optimization problems. Heuristic method, e.g., genetic algorithm, is sought in [32] to solve the problem. A major disadvantage of heuristic methods is that they may arrive at a local optimal solution. To complicate the matter, when optimal sizing and HVAC on/off are considered, integer variables are introduced. This makes problem solving a challenging issue. Prior research related to stochastic MIP can be found in [37, 38]. Branching and bound solving strategy is applied in [37], while Benders decomposition is applied in [38]. In [37], two-stage stochastic programming is employed to determine the optimal scheduling problems for processes of chemical batch. In [39], the authors employed two-stage stochastic programming to determine the optimal offering strategy plans that wind generation plant should consider for its production. The nature of uncertainty of wind power and the uncertainty of energy market price was considered. In [40], Time-of-use (TOU) rates are designed to find the optimal demand response programs options. The authors used two-stage stochastic MIP to accomplish the study. In literature, there are several studies that investigated the battery scheduling problems. In [41], a deterministic mixed integer programming is used to develop an optimal charging schedule by solar panels. In [42], the authors developed an optimal discharging schedule for battery system based on a decision-making algorithm. Commercial solvers such as CPELX or Gurobi are usually adopted. However, very long computing time is expected. For example, in [36], the model was run using 4 parallel CPU threads on a 256 GB RAM server running GAMS 23.0.2 and CPLEX 11.2.1 and the maximum execution time is 10 hours. The second option is heuristic methods. Heuristic methods, e.g., genetic algorithm [32], has the similar scalability issues.

The third option is to use commercial solvers through customized algorithm. For example, branching and bound solving strategy is applied in [37] while Benders decomposition is applied in [38].

Compared to branching and bound method, Benders decomposition is a known efficient algorithm to handle large-scale mixed-integer problems. Benders decomposition has been applied in many power system applications, e.g., unit commitment problems considering wind [38] or transmission constraints [43], transmission planning considering wind [44]. The essential technique is to decompose decision variables into multiple sets [45], e.g., a set of mixed integer variables and a set of continuous variables. For each set of variables, optimization solving will be conducted.

In this chapter, Benders decomposition technique will be adopted for planning and operation of PV/battery/HVAC hybrid systems. A program has been developed and implemented in MATLAB and solved using the CVX solver package [76] and CPELX [77]. The numerical simulation has been performed on a 3.4-GHz based processor with 8GB of RAM and the maximum execution time is 35 minutes. Preliminary work of this research has been reported in [78] where an MIP optimization problem is formulated and Benders decomposition is adopted for solving. In this chapter, parallel computing structure and maximum feasible subsystem cut generation technique are further exploited and implemented to advance the computing. Two variations of Benders decomposition are examined for problem solving. This work proposes an HVAC system powered by a PV-battery system. The decision making process determines the energy and power size of the battery, number of PVs to be installed, and the optimal operating schedule of HVAC units (on/off states). This model is investigated under the uncertainty of the PV-output considering the grid-connected mode while the electricity price is varying. The main contribution of this chapter is modeling the uncertainty of solar energy using stochastic scenarios and solving the large-scale stochastic MIP problem using Benders decomposition. The potential benefits of PV/battery serving HVAC loads are demonstrated in case studies. The proposed formulation has been shown to have the capability to deal with a large number of scenarios. Such a problem cannot be handled by commercial solvers without applying decomposition methods. The rest of the chapter is organized as follows. Section 5.2 presents the HVAC model. Section 5.3 presents the optimization problem formulation. Section 5.4 presents the two variations of Benders decomposition techniques. Section 5.5 presents case studies and Section 5.6 concludes the chapter.

5.2 Thermal Dynamics Models of an HVAC Unit

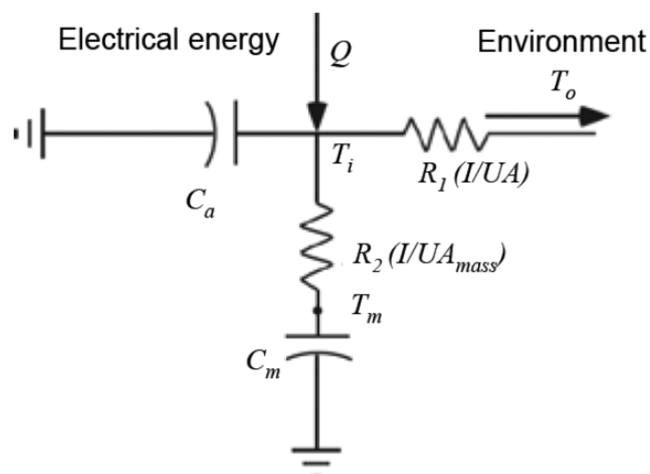

Figure 5.1: The HVAC model.

The equivalent thermal temeprature model of a residential HVAC is shown below in Fig. 5.1 [30], where:

Q	refers to heat rate for HVAC unit (Btu/hr or W).
UA	refers to standby heat loss coefficient (Btu/^{o}F.hr or $W/^o$C).
R_1	refers to 1/UA.
R_2	refers to $1/UA_{mass}$.
T_o	refers to ambient temperature (^{o}F or^{o}C).
T_i	refers to air temperature inside the house (^{o}F or ^{o}C).
T_m	refers to mass temperature inside the house (^{o}F or ^{o}C).
C_a	refers to air heat capacity (Btu/^{o}F or $J/^o$C).
C_m	refers to mass heat capacity (Btu/^{o}F or $J/^o$C).

The above model is further simplified to have one R and one C. When the cooler is turned OFF, the room temperature at time is described by

$$T_{room}^{t+1} = T_o^{t+1} - (T_o^{t+1} - T_{room}^{t}) * e^{-\Delta t/RC} \tag{5.1}$$

The temperature of the room can be calculated when the status of the HVAC is ON as the following:

$$T_{room}^{t+1} = T_o^{t+1} + QR - (T_o^{t+1} + QR - T_{room}^{t}) * e^{-\Delta t/RC} \tag{5.2}$$

T_{room}	refers to room temperature (^{o}F or ^{o}C).
C	refers to equivalent heat capacity (Btu/^{o}F).
R	refers to equivalent thermal resistance (^{o}C/W).
Q	refers to equivalent heat rate (W).
t	refers to air temperature inside the house (minute).
Δt	refers time step (1 minute).

The above two equations will be combined to one thermal constraint through the introduction of a binary variable W^t (1: the cooler is on; 0: the cooler is off).

$$T_{\text{room}}^{t+1} = T_o^{t+1} + W^t QR - (T_o^{t+1} + W^t QR - T_{\text{room}}^{t}) e^{-\frac{\Delta t}{RC}} \tag{5.3}$$

5.3 Optimization Problem Formulation

5.3.1 Treatment of Uncertainty in PV-Output

Scenarios of PV-output are developed based on real-world data collected from the PV panels that are installed at the Saint Petersburg campus of University of South Florida. PV output of a random day is shown in Fig. 5.2.

To reduce computational burden, a tree scenario is created and the probability of each scenario occur is calculated. Then, 600 scenarios with maximum likelihood of occurrence are considered in our analysis. The total probability of those 600 scenarios to occur is more than 88%. The rest 12%

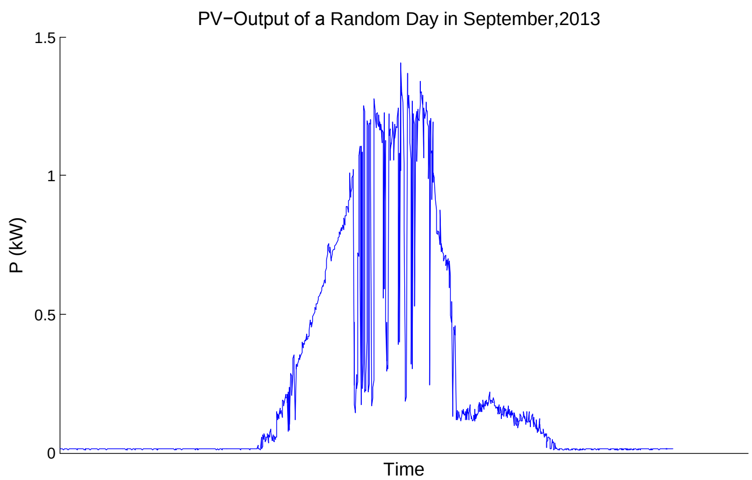

Figure 5.2: PV-output of a random day.

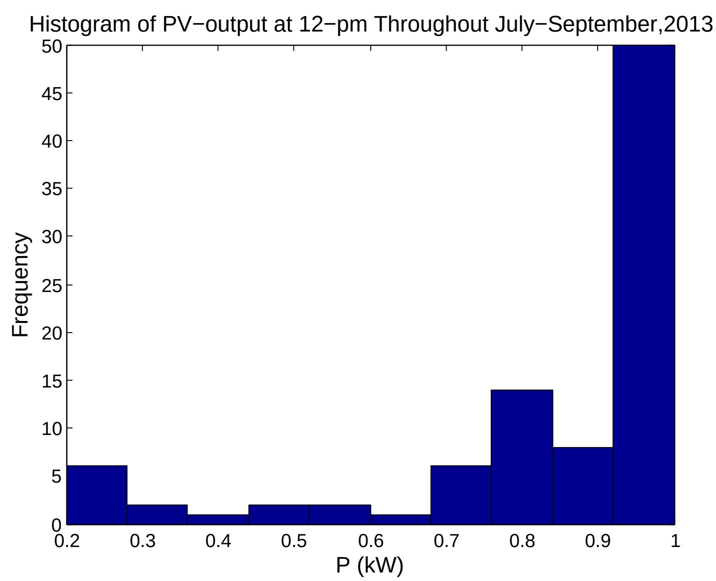

Figure 5.3: Histogram of PV-output at 12 pm based on three months' data.

is divided proportionally among them. Fig. 5.4 shows an example for generating scenarios. In this example, it is assumed that there would be 3 different values of PV-output for the next three time steps. In the three horizons starting from the beginning, the number of total scenarios is 27.

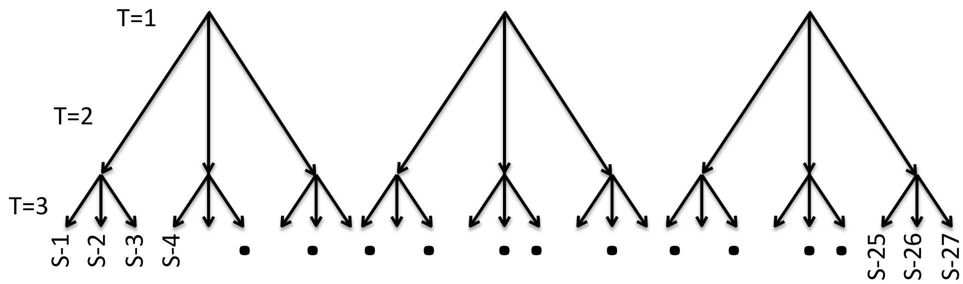

Figure 5.4: Tree scenarios.

5.3.2 Optimization Model

The optimization model is developed based on the assumption that there is a battery energy storage system (BESS) which is installed and can be charged and discharged to store energy from the grid or supply the HVAC with power. In addition, there are PV panels with fixed rate power to be installed. The optimization problem is to determine how many PV panels to be installed and what is the best capacity and power rating for the battery given the system has a number of HVAC with thermal constraints to meet for an 8-hour horizon. The 8-hour horizon is divided into 32 horizons with each horizon 15 minutes.

The assumption of the operation is that the HVAC on/off sequence is not stochastic. Rather, the on/off sequence is deterministic. This assumption is realistic as HVAC's on/off sequence is usually fixed ahead of time. On the other hand, the battery's charging/discharging power level, the smart building's purchased power P_{in} are stochastic scenario based. This is due to the stochastic nature of PV output. The battery power and purchased power level decision is usually made at real-time.

The following three paragraphs give the decision variables, the objective function and the constraints.

5.3.2.1 Decision Variables

The decision variables of this optimization problem will be as the following:

$$X = \left[C_b \;\; E_b \;\; N_{pv} \;\; P_{in}^{s,j} \;\; P_b^{s,j} \;\; W_k^j \right] \tag{5.4}$$

j refers to jth period, $j \in J = \{1, 2, \cdots, 32\}$. 8-hour is considered with each period 15 minutes.

k refers to kth No. of HVAC unit. $k \in K = \{1, 2, 3\}$;

s refers to sth scenario. $s \in S$, where S contains 600 scenarios in the case study.

C_b refers to the power rating of the battery energy system.

E_b refers to the energy rating of the battery energy system.

N_{pv} refers to the power rating of the battery energy system.

$P_{in}^{s,j}$ refers to purchased power at the j-th period of the sth scenario.

W_k^j refers to a binary variable that is equal to 1 if the k-th HVAC is on at the j-th period and 0 otherwise.

$P_b^{s,j}$ refers to the battery power at j-th period of the s-th scenario.

5.3.2.2 Objective Function

$$\min \left\{ \beta_1 C_b + \beta_2 E_b + \alpha N_{pv} + \sum_{j \in J} \sum_{k \in K} W_k^j + \sum_{s \in S} \sum_{j \in J} \rho_s \left(\lambda^j P_{in}^{s,j} \right) \right\} \tag{5.5}$$

β_1 refers to the cost of 1 kW rating of the BESS.

β_2 refers to the cost of 1 kWh rating of the BESS.

α refers to the cost of installation of PV panel.

ρ_s refers to the probability of s-th scenario

λ^j refers to the energy price at the jth period.

5.3.2.3 Constraints

Constraint set (5.6) describes the room temperature dynamics and ensures that thermostat setting is enabled where the temperature of the room must be greater than the minimum temperature and less than the maximum temperature. This constraint set does not contain probability scenarios since the HVAC operation is assumed to be deterministic for the possible scenarios.

$$\begin{aligned}
&T_k^{j+1} = T_o^{j+1} + W_k^j QR - (T_o^{j+1} + W_k^j QR - T_k^j)e^{\frac{-\Delta t}{RC}} \\
&T_{\min} \leq T_k^{j+1} \leq T_{\max} \qquad \forall j \in J
\end{aligned} \tag{5.6}$$

Constraint set (5.8) guarantees that there is enough available power when the HVAC unit is turned on. It also ensures that the purchased power is within the power limits. This set of constraints are scenario-based.

$$P_{in}^{s,j} + P_b^{s,j} + N_{pv} P_{PV}^{s,j} \geq \sum_{i=1}^{k} W_k^j P_{ac,k} \tag{5.7}$$

$$P_{\min} \leq P_{in}^{s,j} \leq P_{\max} \qquad \forall j \in J, \forall k \in K, \forall s \in S \tag{5.8}$$

$P_{ac,k}$ refers to a fixed power consumption for k-th HVAC.

Constraint set (5.9) makes sure that at any hour j and any scenario s, the battery charging or discharging does not exceeding the battery power rating and the energy at any hour will not exceed the energy limits.

$$\begin{aligned}
&- C_b \leq P_b^{s,j} \leq \ C_b \ \ \forall j \in J, \forall s \in S \\
&0 \leq E_0 - \sum_{i=1}^{j} P_b^{s,i} \leq E_b \ \ \forall j \in J, \forall s \in S
\end{aligned} \tag{5.9}$$

5.4 Large-scale Problem Solving Using Benders Decomposition

The optimization problem formulated in Section III is a large-scale problem. The size of the problem increases as the number of scenarios increase. It includes a mixture of integer and continuous variables and would depend on the number of HVAC units, time steps, and scenarios. When 3 HVAC, 32 horizons, and 25 scenarios are considered, the problem has 96 binary variables (related to 3 HVAC units running for 32 time horizons) and one integer variable related to the number of PV. It would also have 99 continuous variables related to the room temperature and two continuous variables related to the battery parameters (C_b and E_b). While all previous variables are independent of the number of scenarios, the number of the other variables depend on the number of scenarios. Those variables include 800 continuous variables (related to the purchased power considering 25 scenarios for 32 time horizons) and 800 continuous variables (related to battery power P_b considering 25 scenarios for 32 time horizons). This formulation is solved using CPLEX in MATLAB and the main challenge here is the very slow computing time (hours).

With 600 scenarios, CPLEX was tested to solve the problem for 24 hours without giving any solution. Therefore, Benders decomposition, an effective method of large-scale MIP problem solving is implemented in this research.

5.4.1 Benders Decomposition with a Single Subproblem

The main philosophy is to separate the decision variables into two sets: those related to HVAC, and those not related to HVAC. The first set includes integer variables including W (which denotes HVAC on/off) and the number of PV, as well as the continuous variables (room temperatures). The second set includes the rest of variables including battery power dispatch level, battery power and energy ratings. The second set variables are all continuous. The solving procedure is to fix Set 1 variables and solve the subproblem related to Set 2. With the solved subproblem, we generate a dual cut to reduce the feasible region of the main problem associated with Set 1 variables. The procedure is kept going until convergence.

In the first step, we assume that the power and energy ratings of a battery, power demand are all zero. Only the HVAC operation is considered. The master problem is formed and we find its optimal solution as follows.

$$\min_{N_{pv}, W_k^j} \quad Z_{\text{lower}} \tag{5.10a}$$

$$\text{s.t. } Z_{\text{lower}} \geq \alpha N_{pv} + \sum_{j \in J} \sum_{k \in K} W_k^j \tag{5.10b}$$

$$T_k^{j+1} = T_o^{j+1} + W_k^j QR - (T_o^{j+1} + W_k^j QR - T_k^j) e^{\frac{-\Delta t}{RC}} \tag{5.10c}$$

$$T_{\min} \leq T_k^{j+1} \leq T_{\max} \;\; \forall j \in J, k \in K \tag{5.10d}$$

In the second step, we form the subproblem and use the obtained optimal solution for the integer variables from the master problem ($\hat{N}_{pv}$, $\hat{W}_k^j$).

$$\min_{\substack{C_b, E_b \\ P_{in}^{s,j} P_b^{s,j}}} \left\{ \beta_1 C_b + \beta_2 E_b + \sum_{s \in S} \sum_{j \in J} \rho_s \left(\lambda^j P_{in}^{s,j} \right) \right\} \tag{5.11a}$$

$$\text{s.t. } \; P_{in}^{s,j} + P_b^{s,j} + \hat{N}_{pv} P_{PV}^{s,j} \geq \sum_{k \in K} \hat{W}_k^j P_{ac,k} \tag{5.11b}$$

$$P_{\min} \leq P_{in}^{s,j} \leq P_{\max} \tag{5.11c}$$

$$0 \leq E_0 - \sum_{i=1}^{j} P_b^{s,i} \leq E_b \tag{5.11d}$$

$$-C_b \leq P_b^{s,j} \leq \; C_b \;\; \forall s \in S, j \in J, k \in K \tag{5.11e}$$

In this step, the subproblem could be infeasible when the available power cannot meet the total demand. In this case, a feasibility cut is generated and added to the master problem as follows:

$$\min_{Y, P_{in}^{s,j}, P_b^{s,j}} \quad \mathbf{1}^T Y \tag{5.12a}$$

$$\text{s.t.} \quad P_{in}^{s,j} + P_b^{s,j} + Y^{s,j} \geq \sum_{k \in K} \hat{W}_k^j P_{ac,k} - \hat{N}_{pv} P_{PV}^{s,j}$$

$$Y^{s,j} \geq 0, , \;\; \forall s \in S, j \in J, k \in K \tag{5.12b}$$

After generating a feasibility cut, $u^s_{r,j}$, the dual associated with this problem is taken. The general form of this cut is:

$$\sum_{s\in S}\sum_{j\in J} u^s_{r,j}\left(\sum_{k\in K} W^j_k P_{ac,k} - N_{pv}P^{s,j}_{PV}\right) \leq 0 \tag{5.13}$$

In the case where the problem is feasible, then the upper bound Z_{upper} is calculated and the convergence behavior is tested. If the convergence is not approached, then an optimality cut is generated and added to the master problem.

$$Z_{\text{upper}} = \left\{\beta_1\hat{C}_b + \beta_2\hat{E}_b + \alpha\hat{N}_{pv} + \sum_{j\in J}\sum_{k\in K}\hat{W}^j_k + \sum_{s\in S}\sum_{j\in J}\rho_s\left(\lambda^j\hat{P}^{s,j}_{in}\right)\right\} \tag{5.14}$$

We assume that $u^s_{p,j}$ are the dual variables associated with constraints (5.11b). Then the optimality cut is formed as the following

$$Z_{\text{lower}} \geq \alpha N_{pv} + \sum_{s\in S}\sum_{j\in J} u^s_{p,j}\left(\sum_{k\in K} W^j_k P_{ac,k} - P^{s,j}_{PV}N_{pv}\right). \tag{5.15}$$

In the third step, the master problem with the added constraints from Step 2 will be solved. The subproblem will again use the obtained optimal solutions for the integer variables from the master problem to solve and find the optimal solution for the other variables. The procedure keeps going until convergence is achieved by examining the low bound Z_{lower} and the upper bound Z_{upper}. Algorithm 1 presents the Benders decomposition strategy. A flowchart of Algorithm 1 is presented in Fig. 5.5.

5.4.2 Benders Decomposition with Multiple Subproblems

Algorithm 1 separates the original problem into a master problem and a subproblem. In this subsection, we further explore the parallel computing structure of the problem and separate the original problem into a master problem with multiple subproblems.

Algorithm 1 Benders Decomposition Strategy 1

initialize $Z_{\text{lower}} = -\infty$ and $Z_{\text{upper}} = \infty$.
for all Iteration i **do**
  Step 1 Solve (5.10) to find the optimal $(\hat{N}_{pv},\hat{W}_k^j)$ and update Z_{lower}
  Step 2 Solve (5.11) for the given set of $(\hat{N}_{pv},\hat{W}_k^k)$.
  while (5.11) is infeasible **do**
    Solve (5.12) to add feasibility constraint(5.13) to (5.10).
    Go to Step 1
  end while
  Find the optimal solution (5.11) and update Z_{upper} (5.14).
  while Convergence is not met **do**
    Solve (5.15) to add optimality constraint to (5.10)
    Go to Step.1
  end while
end for

The main philosophy here is to enable the subproblems to become decomposed over scenarios. Each subproblem is related to a stochastic scenario and the subproblems are independent once the main problem stage variables are determined.

The battery parameters C_b and E_b will be added to the set of the decision variables in the master problem. So the subproblem will only include the rest of the variables including battery power dispatch level and the purchased power for each scenario.

In the first step, we assume that power demand and all battery dispatched level are all zero. Only the HVAC operation and the power and energy ratings of a battery are considered. The master problem is formed as follows.

$$\min_{\substack{C_b,E_b \\ N_{pv},W_k^j}} \quad Z_{\text{lower}} \tag{5.16a}$$

$$\text{s.t.} \quad Z_{\text{lower}} \geq \alpha N_{pv} + \sum_{j\in J}\sum_{k\in K} W_k^j + \beta_1 C_b + \beta_2 E_b \tag{5.16b}$$

$$T_k^{j+1} = T_o^{j+1} + W_k^j QR - (T_o^{j+1} + W_k^j QR - T_k^j)e^{\frac{-\Delta t}{RC}}$$

$$T_{\min} \leq T_k^{j+1} \leq T_{\max} \;\; \forall j \in J, k \in K \tag{5.16c}$$

$$C_b, E_b \geq 0 \tag{5.16d}$$

In the second step, we form the independent subproblems and use the obtained optimal solution for the integer variables from the master problem ($\hat{N}_{pv}$,$\hat{W}_j^k$,$\hat{C}_b$,$\hat{E}_b$). Notice that each subproblem is solved independently. The formulation of a subproblem for a single scenario is given as follows:

$$\min_{P_{in}^{s,j} P_b^{s,j}} \rho_s \sum_{j\in J} \left(\lambda^j P_{in}^{s,j}\right) \tag{5.17a}$$

$$\text{s.t.} \quad P_{in}^{s,j} + P_b^{s,j} + \hat{N}_{pv} P_{PV}^{s,j} \geq \sum_{k=1}^{K} \hat{W}_k^j P_{ac,k} \tag{5.17b}$$

$$P_{\min} \leq P_{in}^{s,j} \leq P_{\max} \tag{5.17c}$$

$$-\hat{C}_b \leq P_b^{s,j} \leq \hat{C}_b \tag{5.17d}$$

$$0 \leq E_0 - \sum_{i=1}^{j} P_b^{s,i} \leq \hat{E}_b, \tag{5.17e}$$

$$\forall s \in S, \forall j \in J, k \in K$$

Maximum feasible subsystem cut generation is considered here. For any infeasible subproblem, we would need to generate the feasibility cut from a maximum feasible subsystem [79]. This strategy makes cut generation highly effective when there are relatively large number of feasibility cuts. The strategy is to generate additional optimality cuts for the infeasible subproblems. This requires to first relax the infeasible subproblems. This technique has been used in [44] for individual stochastic scenarios.

For any infeasible subproblem of Scenario s, we will first relax the problem by finding a binary variable $Y^{s,j}$. If $Y^{s,j} = 0$, that means at j-th horizon the power balance is kept. $Y^{s,j} = 1$ means the power supply cannot mean the power demand where $Y^{s,j}$ is a binary variable and M is a big number. Now, the obtained value $\hat{Y}^{s,j}$ is used to relax the infeasible subproblem.

$$\min_{Y^{s,j}, P_{in}^{s,j}, P_b^{s,j}} \sum_{j\in J} Y^{s,j} \tag{5.18a}$$

$$\text{s.t.} \quad P_{in}^j + P_b^j + Y^j M \geq \sum_{k\in K} \hat{W}_k^j P_{ac,k} - \hat{N}_{pv} P_{PV}^j$$

$$\min_{P_{in}^{s,j} P_b^{s,j}} \rho_s \sum_{j\in J} \left(\lambda^j P_{in}^{s,j}\right) \tag{5.19a}$$

$$\text{s.t.} \quad P_{in}^{s,j} + P_b^{s,j} + \hat{N}_{pv} P_{PV}^{s,j} + \hat{Y}^{s,j} M \geq \sum_{k\in K} \hat{W}_k^j P_{ac,k} \tag{5.19b}$$

$$P_{\min} \leq P_{in}^{s,j} \leq P_{\max} \tag{5.19c}$$

$$-\hat{C}_b \leq P_b^{s,j} \leq \hat{C}_b \tag{5.19d}$$

$$0 \leq E_0 - \sum_{i=1}^{j} P_b^{s,i} \leq \hat{E}_b, \tag{5.19e}$$

$$\forall s \in S, \forall j \in J, k \in K$$

With the optimal solution is obtained, then Z_{upper} is calculated by (5.20) and the convergence behavior is tested.

$$Z_{\text{upper}} = \left\{ \beta_1 \hat{C}_b + \beta_2 \hat{E}_b + \alpha \hat{N}_{pv} + \sum_{j\in J}\sum_{k\in K} \hat{W}_k^j + \sum_{s\in S}\sum_{j\in J} \rho_s \left(\lambda^j \hat{P}_{in}^{s,j}\right) \right\} \tag{5.20}$$

If the convergence is not approached, then an optimality cut is generated and added to the master problem. To create the optimality cut, the dual variables must be extracted. The dual variables are $u_{p,j}^s$ associated with constraints (5.17b), (5.19b), $u_{C,j}^s$ associated with (5.17d), (5.19d), and $u_{E,j}^s$ associated with (5.17e), (5.19e).

The optimality cut is shown as follows.

$$\begin{aligned} Z_{\text{lower}} &\geq \alpha N_{pv} + \sum_{s\in S}\sum_{j\in J} u_{p,j}^s \left(\sum_{k\in K} W_k^j P_{ac,k} - P_{PV}^{s,j} N_{pv} \right) \\ &+ \left(\beta_1 - \sum_{s\in S}\sum_{j\in J} u_{C,j}^s \right) C_b + \left(\beta_2 - \sum_{s\in S}\sum_{j\in J} u_{E,j}^s \right) E_b \end{aligned} \tag{5.21}$$

Algorithm 2 presents the second Benders decomposition strategy. The flowchart of the second Benders decomposition is shown in Fig. 5.6. We can see that for each scenario there is a subproblem to solve and these subproblems can be solved in parallel.

Algorithm 2 Benders Decomposition

initialize $Z_{\text{lower}} = -\infty$ and $Z_{\text{upper}} = \infty$.
for all Iteration i **do**
  Step 1 Solve (5.16) to find the optimal ($\hat{N}_{pv}$,$\hat{W}_k^j$, $\hat{C}_b$, $\hat{E}_b$) and update Z_{lower}.
  for all $s \in S$ **do**
    Step 2 Solve (5.17) for the given the optimal ($\hat{N}_{pv}$,$\hat{W}_k^j$, $\hat{C}_b$, $\hat{E}_b$)
    while ((5.17) is infeasible **do**
      Solve (5.18) (5.19) to add feasibility constraint(5.21) to (5.16)
    end while
  end for
  Solve (5.19) and find the optimal solution
  update Z_{upper} (5.20)
  while Convergence is not met **do**
    Go to Step.1
  end while
end for

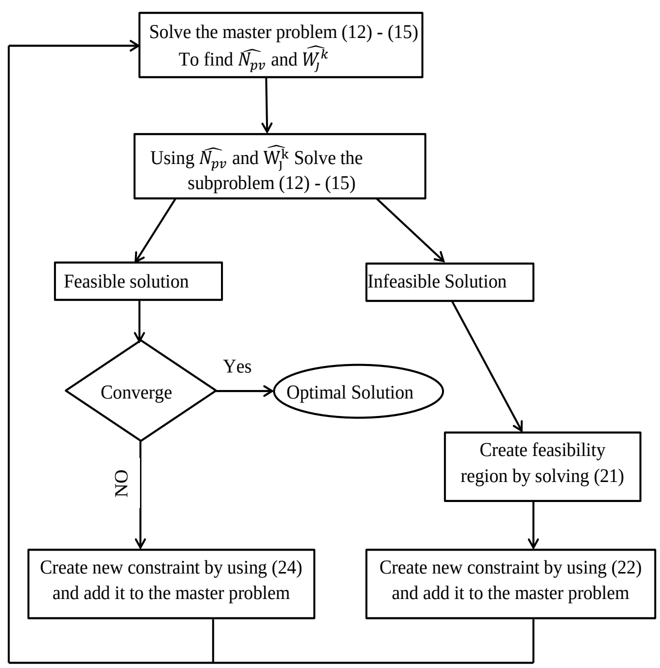

Figure 5.5: Flowchart of strategy-1.

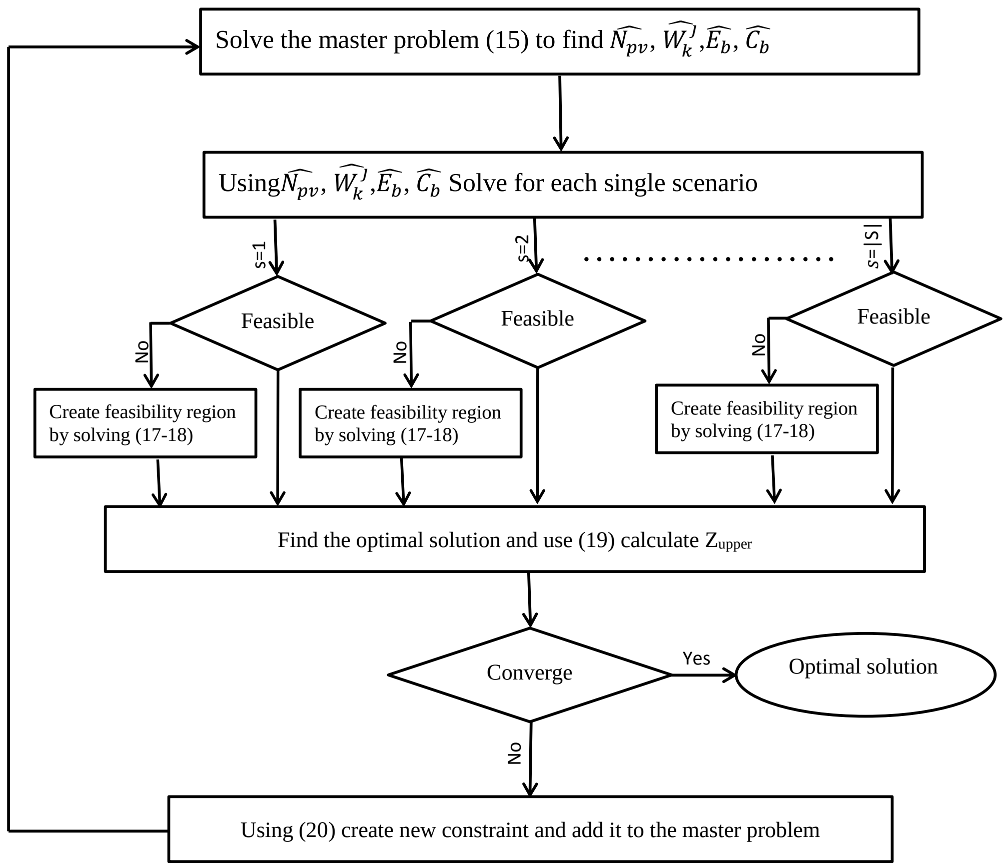

Figure 5.6: Flowchart of the strategy-2.

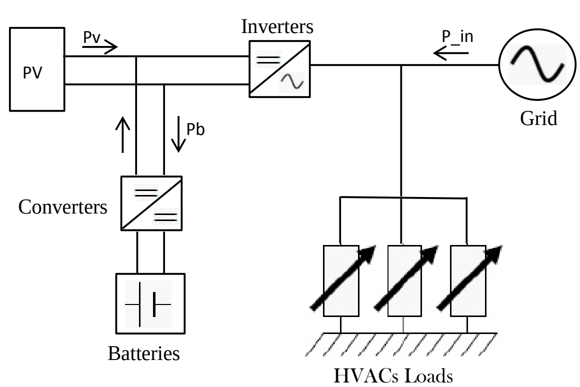

Figure 5.7: The study system of HVAC with PV and power grid.

5.4.3 Benchmark of the Algorithms

We first use a small-scale problem (3 scenarios, 30 binary decision variables, 318 continuous decision variables, and 257 equality constraints) to benchmark the two algorithms. The two Benders decomposition algorithms are programmed and tested against the solution generated by CVX Gurobi. The results from the two algorithms exactly match the objective function result (13.7695) obtained from CVX Gurobi as shown in Fig. 5.8.

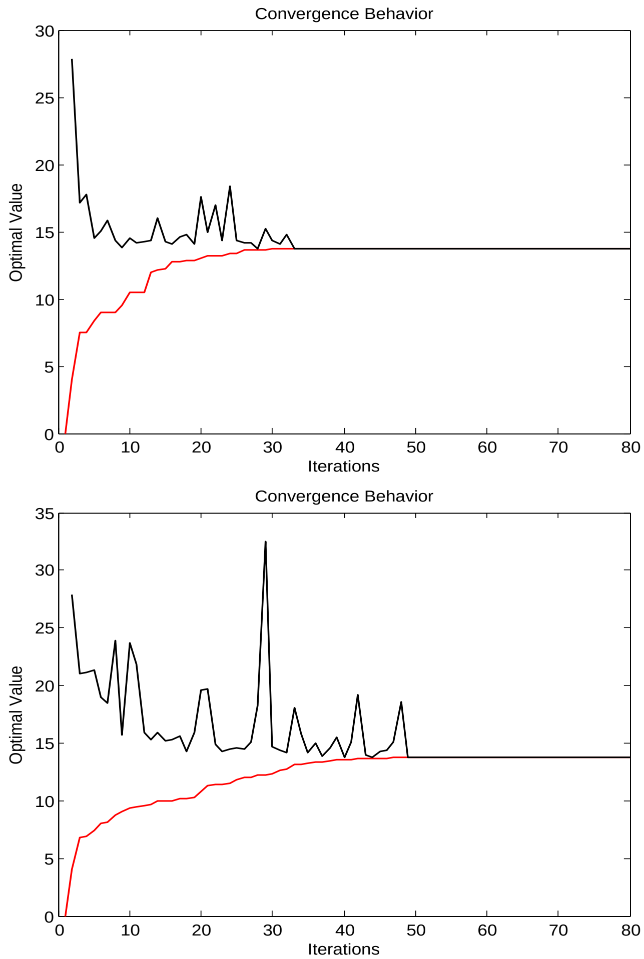

Figure 5.8: (a) Lower and upper bounds of strategy-1 for a small case; (b) lower and upper bounds of strategy-2 for a small case.

5.5 Case Studies and Numerical Examples

5.5.1 The Study System

The study system shown in Fig. 5.7 consists of three HVAC units (rated at 15 kW) in their cooling modes. HVAC units consume electricity from the grid at a varying price, shown in Fig. 5.9, during known periods. Room temperature should be maintained within a defined range by the consumer. Here, the consumer is to set thermostat point settings to 71 F as minimum limit and 75 F as maximum limit. The ambient temperature is shown in Fig. 5.9. The parameters C, R, and Q are shown in Table 5.1.

Table 5.1: Parameter values for HVAC units

	$Q(W)$	$R(F/W)$	$C(J/F)$
Values	400	0.1208	3599.3

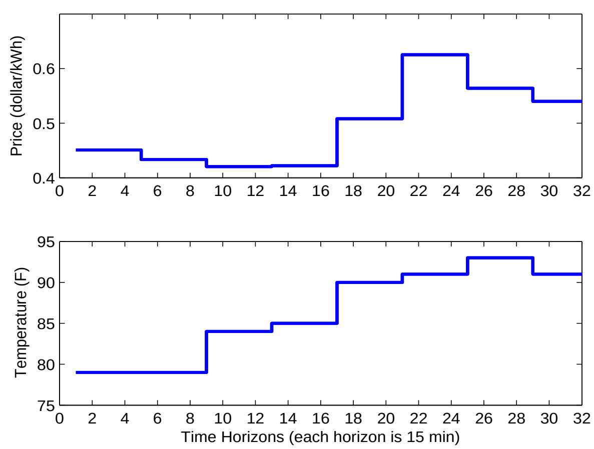

Figure 5.9: Energy price and ambient temperature of 8 hours (32 periods).

5.5.2 Result and Analysis

We consider the system is connected to the grid and can purchase the power from the grid at a varying price. Three cases would be considered to study the effect of the uncertainty. The first case, Case-1, is used to study the behavior of the system without PV-BESS. In the second case Case-2, PV-BESS installation is considered in the deterministic mode to study the effect of solar energy. Two scenarios were studied. The first scenario, Case-2A, is assumed to have high availability of solar energy. The second scenario, Case-2B, is assumed to have poor availability of solar energy. In the third case, Case-3, stochastic MIP programming problem is considered. The proposed method based on Benders decomposition is applied to deal with the uncertainty of solar power. 600 scenarios with the greatest probabilities are considered.

In the fourth case, Case-4, 1500 scenarios are examined. Table 5.2 gives the parameters related to the cost function.

Table 5.2: Cost function parameters

α	β_1	β_2
\$0.5/per panel	\$0.15 /kW	\$0.1 /kWh

The study results are presented in Table 5.3. It can be seen that the deterministic case with high availability of solar energy leads to the cheapest cost.

In Case-3 and Case-4, uncertainty of solar energy is considered. Case-3 and Case-4 lead to the almost same results with slight difference in cost. The difference is due to the consideration of more scenarios in Case-4.

Table 5.3: Simulation results

Case	BESS Rate kWh	BESS Rate kW	N_{pv}	Cost \$
Case-1	N/A	N/A	N/A	30.14
Case-2A	34.8	8.7	7	20.80
Case-2B	43.8	10.8	14	25.5
Case-3	37.6	9.40	7	22.32
Case-4	37.6	9.40	7	23.24

Fig. 5.10-a shows that the optimal value converges to \$22.32 when Benders decomposition Strategy-1 method is applied. Fig. 5.10-b shows that the optimal value converged to \$23.24 when Benders decomposition Strategy-2 method applied.

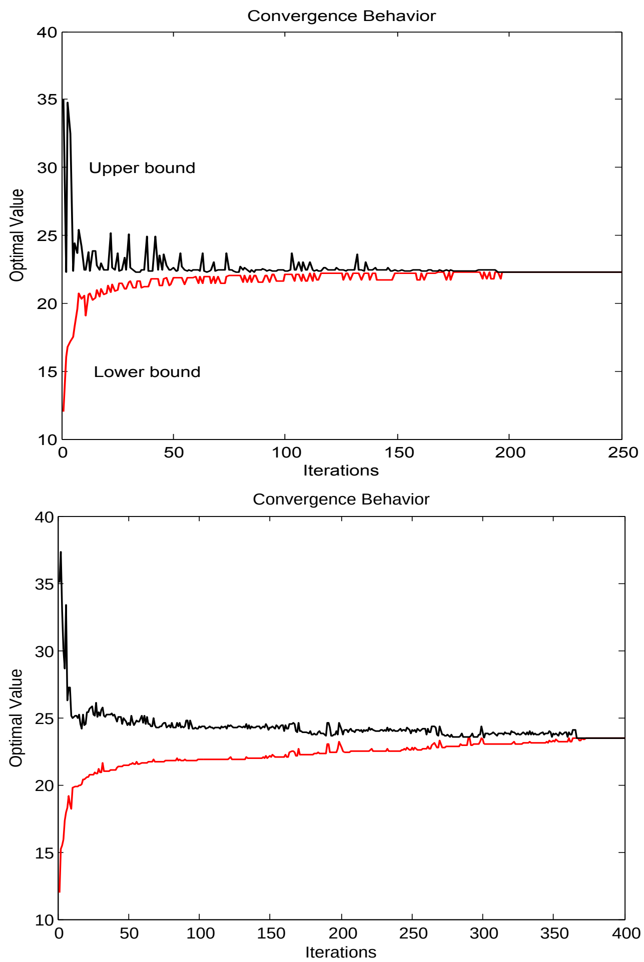

Figure 5.10: (a) Lower and upper bounds of strategy-1 for a large case; (b) lower and upper bounds of strategy-2 for a large case.

Fig. 5.11 presents the HVAC on/off schedule and the room temperature. Fig. 5.12 presents the numerical results for two extreme cases. The good scenario refers to the scenario when PV output is high while the bad scenario refers to the scenario when PV output is low.

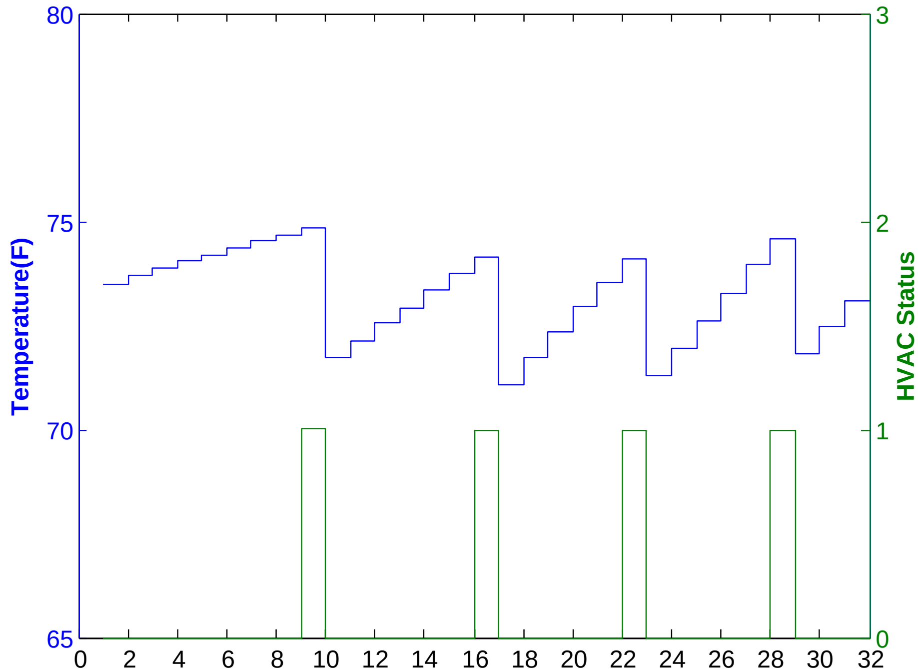

Figure 5.11: HVAC on/off schedule and temperature.

Then, we this study shows an extreme case that prices of battery are cheap so we can can investigate its impact on the purchased power. Fig. 5.13 shows that power can be still purchased at high energy price and that can be explained as the battery price is limitting installing a greater size. However, Fig. 5.13 shows that when we use low price for the battery, then it can be considered as relaxation for the battery constraints and can allow for installing greater size of battery. Then, it can be seen that the power is purchased at the lowest energy price.

5.5.3 Computational Time

A program has been developed and implemented in MATLAB and solved using the CVX solver package and CPLEX. The numerical simulation has been performed on a 3.4-GHz based processor with 8GB of RAM. Stochastic Mixed Integer Programming (SMIP) is developed to tackle the

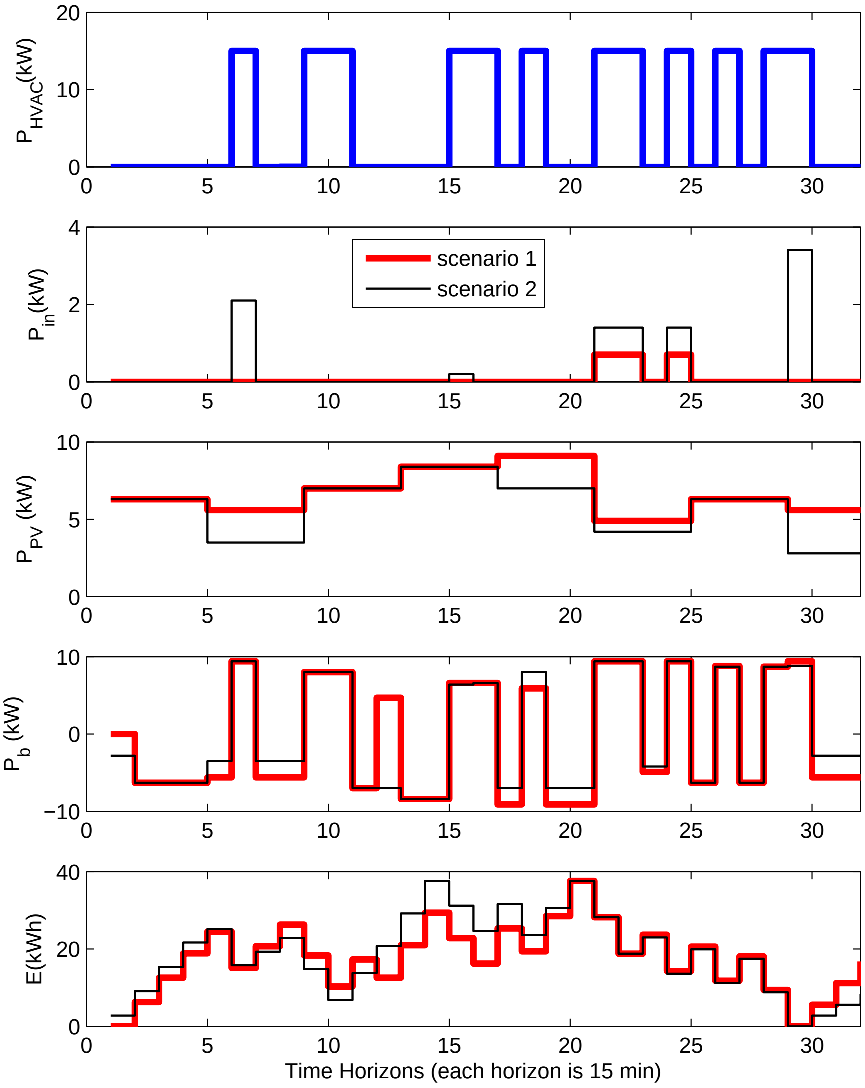

Figure 5.12: PV output power, battery power, battery energy and purchased power for two extreme cases.

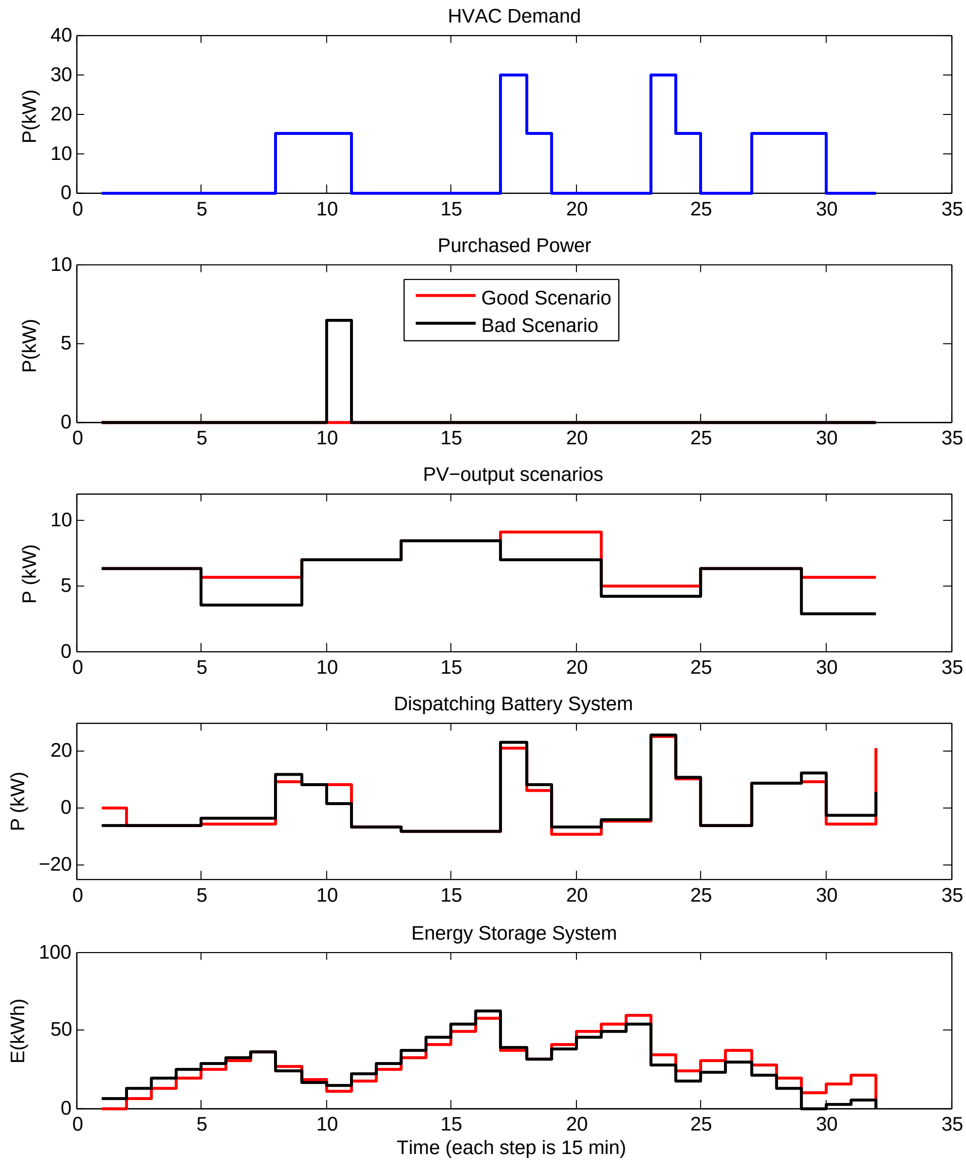

Figure 5.13: PV output power, battery power, battery energy and purchased power for two extreme cases when battery price is low.

uncertainty. It is first solved as one original problem without any decomposition. The size of the problem increases as the number of scenarios increase. It includes a mixture of integer and continuous variables and would depend on the number of HVAC units, time horizons, and scenarios. This formulation is solved using CPLEX in MATLAB and the main challenge here is centered in the large number of the constraints of the power balance with integer variables.

Two Benders decomposition methods are also applied to solve the problem. A comparison of the three methods on problem size and computing time is shown in Table 5.4. In strategy 1, the

Table 5.4: Problem size and computing time

	Variables	SMIP 25 scen.	Strategy 1 600 scen.	Strategy 2 1500 scen.
Original	Integer	97	97	97
	Continuous	1701	38501	96101
Master	Integer	-	97	97
	Continuous	-	99	101
Sub Prob	Integer	-	0	0
	Continuous	-	38402	96000
Time	min	390	35	150

problem is decomposed in a master problem and a subproblem. The size of the master problem is constant and it includes a mixture of integer and continuous variables and would depend on the number of HVAC units, and the time steps. When considering 3 HVAC and 32 time-steps,the problem would have 96 binary variables (related to 3 HVAC units running for 32-time steps) and one integer variable related to the number of PV. It would also have 99 continuous variables related to the room temperature. The size of the subproblem increases as the number of scenarios increase. It only includes continuous variables and would depend on the number of time-steps and the number of scenarios. In our case, we consider 32 time-steps and 600 scenarios. This would yield to 19200 continuous variables related to the purchased power considering 600 scenarios for 32-time steps and 19200 continuous variables related to battery power P_b. It also includes two continuous variables related to the Battery parameters (C_b and E_b).

This formulation is firstly solved using CVX for both the master and the sub problems. The advantage of CVX is its ability of returning dual variables along with primal variables. However, when the number of scenarios increases, CVX starts to have difficulty of solving. Therefore, a

CPLEX formulation is used for the master problem to tackle this challenge and CVX is used solving the subproblem. This strategy can work with a number of scenarios up to around 600. When the number of the scenarios increase, the size of the subproblem gets much larger and solving becomes more challenging.

Strategy 2 is different from Strategy 1 by moving the two continuous variables related to the Battery parameters (C_b and E_b) from the subproblem to the master problem. While in Strategy 1, the subproblem is considered as one whole problem including all variables, the subproblem in Strategy 2 is decomposed into multiple subproblems with each representing a scenario. This structure allows us to consider greater number of scenarios. Here, we are able to consider 1500 scenarios which would yield to have 48000 continuous variables (related to the purchased power considering 1500 scenarios for 32-time steps) and 48000 continuous variables related to battery power P_b. It also includes two continuous variables related to the Battery parameters (C_b and E_b). In this problem, the computing challenge is tackled by decomposing the subproblem in multiple subproblems. Therefore, CVX is able to solve those subproblems sequentially. Strategy 2 shows the capability of handling 1500 scenarios while the Strategy 1 keeps running with no return when considering the same number of scenarios.

5.6 Conclusion

In this chapter, stochastic mixed integer programming optimization problems are formulated to determine the optimal sizing of PV-BESS to power HVAC loads. Benders decomposition is used to solve the problem and deal with the uncertainty of PV-output. The optimization problem can find the optimal HVAC on/off states, and BESS charging- discharging states for a multi-horizon period. The main contribution of this chapter is modeling the uncertainty of solar energy and application of Benders decomposition to investigate the potential benefits of PV-BESS with HVAC loads. This formulation has shown a great ability to deal with a large number stochastic scenarios.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

This dissertation can be concluded in three parts as follows.

First, chapter 3 presents MIP problem formulation to find the size of a BESS. The BESS could be owned by a utility to reduce the operation cost or owned by a community for peak shaving. Switchable loads are considered in the problem formulation and unit commitment is also considered. Objective functions, linear constraints for BESS and switchable load constraints suitable for MIP solving are defined. The optimization problems are solved by commercial tool CPLEX. Case study results demonstrate the impact of switchable load penetration on BESS size. It is found that for the system studied, with 5% penetration of switchable loads, the size of energy storage can be cut down 30%. In addition, the size of the energy storage can also be determined based on multiobjective optimization of imported power deviation and battery cost. If we can tolerate 4% power deviation, we can cut down the size of a BESS by 10%.

Second, the Smart Grid is emerging, and buildings of the future will need Smart Consumption technologies to fully realize its benefits. In chapter 4, models are proposed which can help end users' to participate in decision making to better manage their energy consumption in an efficient way. That would increase their participation to achieve an effective demand response which is one of the main goals of Smart Grid. The results of installing a BESS has shown that such approach can provide a different alternative which allows costumers to minimize the total cost of their energy consumption. Different forms of load management are demonstrated as the HVACs show potentiality to be a great tool for load management purposes while they are still capable to satisfy all of thermal and other constraints.

Third, in chapter 5, stochastic mixed integer programming optimization problems are formulated to determine the optimal sizing of PV-BESS to power HVAC loads. Benders Decomposition is used to solve the problem and deal with the uncertainty of PV-output. The optimization problem can find the optimal HVAC on/off states, and BESS charging- discharging states for a multi-horizon period. The main contribution of this chapter is modeling the uncertainty of solar energy and application of Benders decomposition to investigate the potential benefits of PV-BESS with HVAC loads. This formulation has shown a great ability to deal with a large number stochastic scenarios.

6.2 Future Work

Those models can be extended to study the feasibility of participation of customers in the power market. Demand response programs can enable the customers to participate and react to the energy market changes especially to the dynamic pricing mechanism and the changes in the electricity prices. Utilities which want to compete in the energy market, whose structure at the current time is competitive, need to consider those programs. By considering such programs, they can reduce their cost and increase the grid reliability. Locational marginal Price which represents an important component of the electricity market is sensitive to the generation, congestion and demand. When demands change then it is expected to have some impacts on the LMP. In future work, the impacts of demand response penetration and the storage energy that can have on LMP must explored by utilities. They also need to explore the benefits they can get from those programs to gain more flexibility to control the voltage level and make the grid more stable. These models can be extended to investigate the feasibility of deferring building power plants, transmission lines, or distribution networks. Another work related to frequency control can be studied by extending those models. The grid frequency is highly expected to be instable due to the increasingly growing renewable generation and the nature of uncertainty associated with such sources,in case that the grid is not prepared for such penetration. Therefore, it is a great idea to extend those models to study how to tackle the frequency control by implementing optimal demand response models.

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APPENDICES

Appendix A Matlab Code for Benders Decomposition

```
clear all;
clc;
load 'PV_DATA';
RZlow=0;
R2=0;
lambda2=zeros(1,32);
lambda3=zeros(1,32);
DD20=0
CC20=0
Cost_cb=0.15;
Cost_Eb=0.10;
P_ac=15;
CA5=zeros(3200,1);
PriceA=[0.4508 0.4336 0.4204 0.4220 0.5080 0.6256    0.5640    0.5400];
Tout= [79 79 84 85 90 91 93 91 ];
P_b=inf;
Q=-100.5*(1-exp(-15/434));Q1=exp(-15/434);Q2=(1-exp(-15/434));
Cpv=0.5;
n=4
PV=PV(1:600,1:32);
ps=((ps(1:600)+.0002765*ones(600,1)));
for k=1:1:8
    for j= 1:1:n
        Price(n*(k-1)+j)=PriceA(k);
        To(n*(k-1)+j)=Tout(k);
    end
```

```
end
for k=1:1:8
    for j= 1:1:n
        Price(n*(k-1)+j)=PriceA(k);
        To(n*(k-1)+j)=Tout(k);
    end
end
f=[1;ones(8*n,1);zeros(8*n+1,1);ones(8*n,1);zeros(8*n+1,1); ...
    ones(8*n,1); zeros(8*n+1,1);Cpv];
T1max=[73.5;75*ones(8*n,1)];T1min=[73.5;71*ones(8*n,1)]; ...
    T2max=[73.2;75*ones(8*n,1)];T2min=[73.2;71*ones(8*n,1)]; ...
    Emin=[zeros(8*n,1)];
    Emax=[25*ones(8*n,1)];
T3max=[73.8;75*ones(8*n,1)];T3min=[73.8;71*ones(8*n,1)];

for MM=1:1:2
t4=[-1 ones(1,8*n) zeros(1,8*n+1) ones(1,8*n) zeros(1,8*n+1) ones(1,8*n)...
    zeros(1,8*n+1) Cpv];
for k=1:1:8*n
      t1(k,:)=[0  zeros(1,k-1) -Q zeros(1,8*n-k) zeros(1,k-1) -Q1  1 ...
          zeros(1,8*n-k) zeros(1,8*n) zeros(1,8*n+1)  zeros(1,8*n) ...
          zeros(1,8*n+1) 0]; % T2-T1-u1-u2=Tout
      t2(k,:)=[0  zeros(1,8*n) zeros(1,8*n+1) zeros(1,k-1) -Q ...
          zeros(1,8*n-k) zeros(1,k-1) -Q1  1 zeros(1,8*n-k)  ...
          zeros(1,8*n) zeros(1,8*n+1) 0]; % T2-T1-u1-u2=Tout
      t3(k,:)=[0  zeros(1,8*n) zeros(1,8*n+1) zeros(1,8*n) ...
```

```
          zeros(1,8*n+1) zeros(1,k-1) -Q zeros(1,8*n-k) zeros(1,k-1)...
          -Q1  1 zeros(1,8*n-k)  0]; % T2-T1-u1-u2=Tout
end
for kk=1:1:MM
 t5(kk,:)=[RZlow(kk)*-1 (ones(1,32)+(lambda2(kk,:)))*RZlow(kk) ...
     zeros(1,8*n+1) (ones(1,32)+(lambda2(kk,:)))*RZlow(kk) ...
     zeros(1,8*n+1) (ones(1,32)+(lambda2(kk,:)))*RZlow(kk) ...
     zeros(1,8*n+1) (Cpv+DD20(kk,1))*RZlow(kk)];
 b5(kk,:)=0;
 t6(kk,:)=[0 (ones(1,32)+(lambda3(kk,:)))*R2(kk) zeros(1,8*n+1) ...
             (ones(1,32)+(lambda3(kk,:)))*R2(kk) zeros(1,8*n+1) ...
             (ones(1,32)+(lambda3(kk,:)))*R2(kk) zeros(1,8*n+1) ...
             (Cpv+CC20(kk,1))*R2(kk)];
 b6(kk,:)=0;
end
Ctype1='CIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIICCCCCCCCCCCCCCCCCCCCCCCCC ...
        CCCCCCCCIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIICCCCCCCCCCCCCCCCCC ...
        CCCCCCCCCCCCCCCIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIIICCCCCCCCCCC ...
        CCCCCCCCCCCCCCCCCCCCCCI';
ctype=Ctype1;
Aineq=[t4;t5];bineq=[0;b5];
Aeq=[t1;t2;t3];beq=[Q2*To';Q2*To';Q2*To'];
lb=[0;zeros(8*n,1);T1min;zeros(8*n,1);T2min;zeros(8*n,1);T3min;0];
ub=[inf;ones(8*n,1);T1max;ones(8*n,1);T2max;ones(8*n,1);T3max;inf];
[X,fval,exitflag,output] = cplexmilp(f,Aineq,bineq,Aeq,beq,[],[],[] ...
    ,lb,ub,ctype);
```

```
W1=X(2:33);W2=X(67:98);W3=X(132:163);Npv=X(197);
Z1_lower(MM)=X(1);
Z_lower=X(1);
for ss=1:1:600
    CA(:,(ss-1)*32+1:ss*32)=ps(ss)*Price/4;
    CA2((ss-1)*32+1:ss*32,:)=W1;
    CA3((ss-1)*32+1:ss*32,:)=W2;
    CA4((ss-1)*32+1:ss*32,:)=W3;
    CA5((ss-1)*32+1:ss*32,:)=PV((ss),:);
end
cvx_begin
       cvx_solver Gurobi_2
       variables P(19200)  Pb(19200) Cb Eb;
       dual variables lambda
       minimize CA*P+Cost_cb*Cb+Cost_Eb*Eb
       lambda: P>=(CA2*P_ac+CA3*P_ac+CA4*P_ac)-Pb-(Npv*CA5);
       P>=0
       -Pb>=-Cb;
       Pb>=-Cb;
       Cb<=.25*Eb;
       for KL=1:1:600
       [-tril(ones(32,32))]*Pb((KL-1)*32+1:32*KL)>=0;
       [tril(ones(32,32))]*Pb((KL-1)*32+1:32*KL) >=-Eb;
       end
cvx_end
if cvx_optval==inf
```

```
cvx_begin
cvx_solver Gurobi_2
       variables P(19200)  Pb(19200) Y(30) Cb Eb;
       dual variables lambda_3
       minimize ones(1,30)*Y
       lambda_3: P+Y>=([W1;W1;W1]*P_ac+[W2;W2;W2]*P_ac+[W3;W3;W3] ...
           *P_ac)-Pb-(Npv*[PV1;PV2;PV3]);
       Y>0;
       P>=0
       P<=4
       -Pb>=-Cb;
       Pb>=-Cb;
       Cb<=.25*Eb;
       [-tril(ones(10,10)) zeros(10,20);zeros(10,10) -tril(ones(10,10)) ...
           zeros(10,10);zeros(10,20) -tril(ones(10,10))]*Pb>=0;
       [tril(ones(10,10)) zeros(10,20);zeros(10,10) tril(ones(10,10)) ...
           zeros(10,10);zeros(10,20) tril(ones(10,10))]*Pb>=-Eb;
cvx_end
for WL=1:1:600
    B2(:,WL)=lambda_3((WL-1)*32+1:WL*32);
end
    lambda3(MM+1,:)=P_ac*[sum(B2,2)];
for WL1=1:1:600
    B3((WL1-1)*32+1:WL1*32)=PV(WL1,:);
end
    CC20(MM+1,1)=-B3*lambda_3;
```

```
    RZlow(MM+1)=0;
    R2(MM+1)=1;
    lambda2(MM+1,:)=zeros(1,32);
    DD20(MM+1,1)=0
    Z1_upper(MM)=inf;
else
  Z1_upper(MM)=ones(1,32)*W1+ones(1,32)*W2+ones(1,32)*W3+Cpv*Npv ...
      +cvx_optval;
  Z_upper=ones(1,32)*W1+ones(1,32)*W2+ones(1,32)*W3+Cpv*Npv ...
      +cvx_optval;;
  for WL=1:1:600
    B2(:,WL)=lambda((WL-1)*32+1:WL*32);
  end
    lambda2(MM+1,:)=P_ac*[sum(B2,2)];
  for WL1=1:1:600
    B3((WL1-1)*32+1:WL1*32)=PV(WL1,:);
  end
  lambda3(MM+1,:)=zeros(1,32);
  CC20(MM+1,1)=0;
  DD20(MM+1,1)=-B3*lambda;
  RZlow(MM+1)=1;R2(MM+1)=0;
  MM
  Z_lower
  Z_upper
end
end
```

```
figure(1)

plot(1:MM,[Z1_lower],'-r*','LineWidth',1.0);

hold on

plot(1:MM,[Z1_upper],'-x','LineWidth',1.0);

Number_of_pv=Npv

Battery_power_rating=Cb

Battery_Energy_rating=Eb
```

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Mohemmed Alhaider obtained B.S degree in Electrical Engineering from King Abdulaziz University in Saudi Arabia in 2003. After graduation He worked as an Operation Engineering in Najran Power Plant until 2009. He joined the Master's program of Electrical Engineering at University of South Florida. He obtained the Master's degree in May, 2011. After that, he immediately joined PhD program and has been working under supervision of Dr. Fan at Smart Grid Power Systems Lab. Mohemmed is a student member of IEEE and his area of interest includes applications of optimization in power systems, storage energy applications, demand response and smart grids.