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Managing risks of market price uncertainty for a microgrid operation

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MANAGING RISKS OF MARKET PRICE UNCERTAINTY FOR A MICROGRID OPERATION

by

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ABSTRACT

After deregulation of electricity in the United States, the day-ahead and real-time markets allow load serving entities and generation companies to bid and purchase/sell energy under the supervision of the independent system operator (ISO). The electricity market prices are inherently uncertain, and can be highly volatile. The main objective of this thesis is to hedge against the risk from the uncertainty of the market prices when purchasing/selling energy from/to the market. The energy manager can also schedule distributed generators (DGs) and storage of the microgrid to meet the demand, in addition to energy transactions from the market. The risk measure used in this work is the variance of the uncertain market purchase/sale cost/revenue, assuming the price following a Gaussian distribution. Using Markowitz optimization, the risk is minimized to find the optimal mix of purchase from the markets. The problem is formulated as a mixed integer quadratic program. The microgrid at Illinois Institute of Technology (IIT) in Chicago, IL was used as a case study. The result of this work reveals the tradeoff faced by the microgrid energy manager between minimizing the risk and minimizing the mean of the total operating cost (TOC) of the microgrid. With this information, the microgrid energy manager can make decisions in the day-ahead and real-time markets according to their risk aversion preference. The assumption of market prices following Gaussian distribution is also verified to be reasonable for the purpose of hedging against their risks. This is done by comparing the result of the proposed formulation with that obtained from the sample market prices randomly generated using the distribution of actual historic market price data.

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1. INTRODUCTION

A microgrid is a localized group of interconnected loads and distributed energy resources (DER) with the ability to isolate from the main grid and operate autonomously during disturbances in the main grid [1]. The concept of microgrids improved the reliability in applications such as defense, telecommunication, hospitals, etc. They also support the operation of greener energy resources such as solar, wind and other renewable energy resources. With the ability to generate and consume energy, they are often considered as prosumers. With ISOs such as California ISO allowing distributed energy resources to bid into markets [2], this work explores the role of a microgrid as a market player. The property of prosumption makes the role of a microgrid more interesting when bidding into the day-ahead and real-markets as they can both purchase as well sell energy as a single entity. The framework of the problem in this work defines the microgrid as a direct participant in the market as shown in Figure 1.1.

The motivation of this work is to solve the problem of the Microgrid Energy Manager (MEM) through three main objectives. Firstly, the problem of microgrid energy scheduling. Secondly, propose a method to manage the problem of market price uncertainty in the day-ahead and real-time markets. Thirdly, to verify and study the tradeoff faced by the MEM between risk and the TOC of the microgrid.

MEMs work to provide a safe, reliable and cost-effective operation of microgrids. With the historic and forecasted solar insolation, wind speed, load and market price data, the MEM works to minimize the expected TOC to meet the demand at a given period of time. In the first objective of this work, the end demand is considered to be met by the generation of DERs and by purchasing energy from the wholesale electricity market. Hence the TOC of a microgrid includes the cost of operating the DERs as well as the market purchase cost.

In the wholesale energy market, price-quantity bids from the generation companies (to sell power) and load serving entities (to buy power) are acquired by the system operator to solve for the locational marginal price [3]. The day-ahead market price-quantity is cleared a day ahead in an hourly interval based on the system load forecast. To meet the difference in the forecast and actual demand, the real-time market is cleared every 5 minutes after the actual demand of the system. The electricity market prices are inherently uncertain, and can be highly volatile. Generation outages and transmission congestion are a few reasons for the price uncertainty. With recent advancements in the grid such as increased renewable energy penetration, such as solar and wind energy and programs such as demand side managements have made the electricity price more uncertain and difficult to forecast [4].

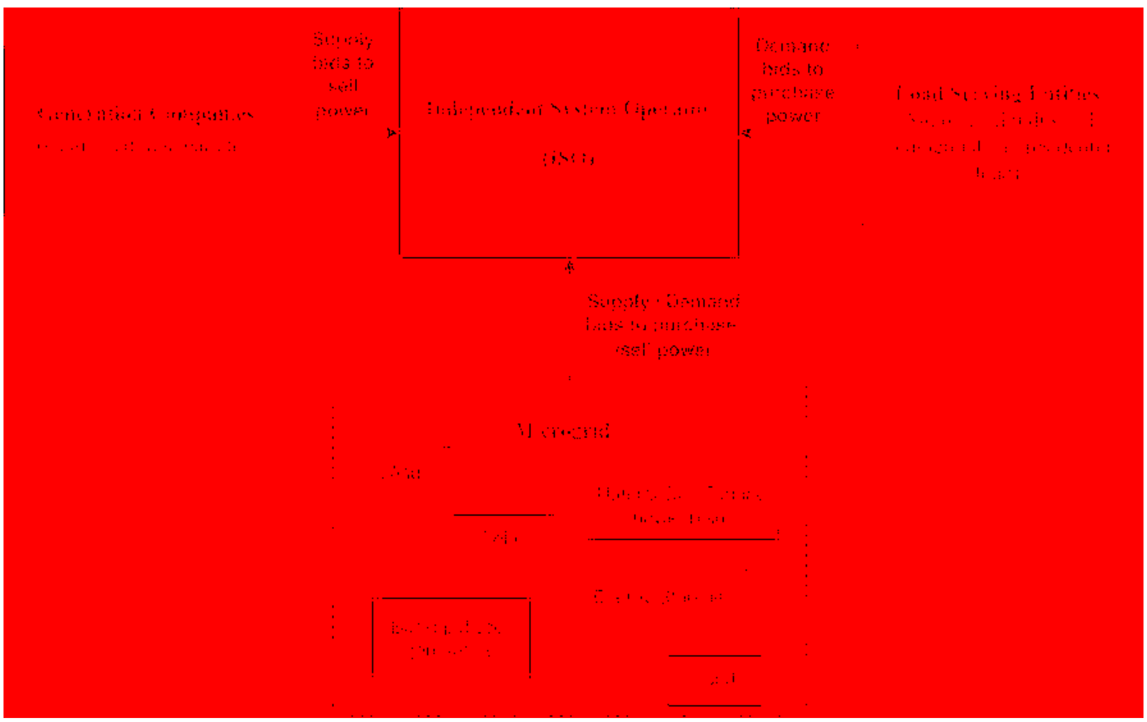

Figure 1.1. Optimal power trading of a microgrid in wholesale electricity market

The decision of the MEM to purchase/sell energy to the grid becomes complicated when considering uncertainty of the market price. As the first objective of this work was to optimally schedule energy, it is important that the MEM manages the risks from the market price uncertainty to buy/sell energy. Hence it is important to develop a framework that handles the market price uncertainty so that it ensures a minimized risk operation of the microgrid which serves as the second objective of this work.

A lot of work has been done on managing the price uncertainty for generation companies to bid in the wholesale electricity markets. The problem of a generation company taking part in a day-ahead, real-time and ancillary markets is solved in [5]. The Condition Value at Risk (CVaR) is defined as the measure of the market risk. The tradeoff faced by the generation company between achieving profits and exposure to risk is explored. A multi-stage mixed-integer stochastic problem is solved for the Italian market model as a case study to analyze the risk/return tradeoff. With a similar motivation of solving the problem of a generation company participating in the energy market, an optimal bidding strategy is developed in [6]. The uncertainty in the market prices is modeled using the scenario approach. Monte Carlo simulation is used to generate scenarios and the size of the stochastic optimization problem is reduced using scenario reduction techniques. The risk associated with the market price uncertainty is modeled using expected downside risk, and is formulated as a constraint to the optimization problem. [7] also solves a similar problem of a generation company trying to maximize the profit while minimizing the risk associated with the market price uncertainty. A multi-objective particle swarm optimization problem is proposed for thermal generation companies to schedule their production in a day-ahead electricity market and is solved for the PJM ISO/RTO’s (Regional Transmission Organization) market price uncertainty as a case study. The tradeoff between risk and return of a generation company is described in [8] by introducing a risk penalty factor based on the profits made by the generation company. An analytical approach to manage the production of power for multiple markets taking various uncertainties such as fuel price volatility, electricity price, etc. was proposed. In [9], for the same objective, uncertainty is modeled via scenarios generated by an input/output hidden Markov model.

A considerable amount of work has been done managing the risk/uncertainty from the load serving entity/aggregator or from a MEM's point of view. [4] presents a model predictive control based operation strategy to manage the uncertainty due to high penetration of renewable energy resources. This paper solves the problem of a load serving entity with energy storage system to manage the price volatility in both day-ahead and real-time markets. An optimization framework that balances the maximizing the return and minimizing the operational cost of a microgrid is proposed in [10]. The energy scheduling problem is formulated as a two-stage stochastic program where various uncertainties are captured by the Monte Carlo simulation approach. The problem of a load serving entity managing the risk associated with market price volatility in spot markets with demand response is discussed in [11]. The authors propose a new concept using Markowitz optimization that looks into the correlated risks between the day-ahead and real-time markets.

As pointed out in [11], most of the previous works do not take into account the correlation of the market prices. The hourly market prices are not only dependent within a single market but between different markets as well. It is important to take this correlation into account when dealing with the market price uncertainty and hence is included in this work. The correlation between the hourly market prices can be realized by constructing a covariance matrix for the hourly market prices as shown later in this work. Most of the previous work do not explore the problem of a MEM facing market price uncertainty and the works related to solving this problem do not take into account the market price correlations. The problem formulation in this work is novel in the sense that it minimizes the risk/uncertainty by taking the market price correlation approach to schedule the energy of the DERs in a microgrid, as a direct participant in the market. Assuming that the market prices follow a Gaussian distribution, the Markowitz optimization is used to find the optimal mix of purchase from the markets by minimizing the risk associated with both day-ahead and real-time markets [12].

The final and the third objective of this work is to analyze the tradeoff between the risk and expected TOC of the microgrid. There is always the tradeoff between the risk and return of any investment, and hence it is important to see the tradeoff the MEM faces. According to the risk-return tradeoff, an investment can render greater profits if it is subject to the possibility of higher risks. This work considers that the MEM has 48 different assets, (24 hourly investments for day-ahead and real-time markets), and with given risk/return for each asset, the problem solves for the amount of energy that needs to be purchased/sold from/to the wholesale electricity market that is of maximum profit to the MEM. Another important part of this analysis is to check for the assumption of the market prices following the Gaussian distribution is a reasonable one. In reality, the market prices do not follow a Gaussian distribution. The assumption of market prices following Gaussian distribution is also verified to be reasonable for the purpose of hedging against their risks. This is done by comparing the result of the proposed formulation with that obtained from the sample market prices randomly generated using the distribution of actual historic market price data.

2. PROBLEM FORMULATION OF THE MICROGRID ENERGY MANAGER

The objective of the microgrid energy manager (MEM) is to meet the load of microgrid in the most economical way. The energy scheduling problem is formulated to find the optimal power generation from the DERs and the optimal mix of purchase from both day-ahead and real-time markets required to meet the load for 24 hours. The problem is solved before the day-ahead market is settled, so the prices of both day-ahead and real-time markets are uncertain.

The market price uncertainty complicates the decision of the MEM on the quantity needed to purchase from both the markets to meet the load. This work considers the variance of the purchase cost as a risk measure to manage the market price uncertainty. Hence, the objective function of the energy scheduling problem is to minimize the risk/variance of the market prices (both the day-ahead and the real-time market) as well the mean of the TOC of the microgrid. The TOC of a microgrid is the cost associated to run all the DERs and the purchase from the grid to meet the load over the given time period.

This section builds the different blocks of the objective function and the constraints for the mixed integer quadratic program that the MEM solves to schedule the DERs and to find the optimal purchase from both markets to meet the load. It is organized as follows:

- First, the objective function that calculates the optimal mix for purchase from day-ahead and real-time markets using Markowitz optimization is formulated.
- Secondly, the covariance matrix of the day-ahead and real-time market price is constructed.
- And lastly, the problem of distributed energy scheduling problem along with the constraints is formulated.

2.1. OBJECTIVE FUNCTION USING MARKOWITZ OPTIMIZATION

The objective function with respect to the market purchase cost consist of two important parts, the risk and mean of the market purchase cost. According to Markowitz optimization [12], the objective is to minimize the risk/variance and maximize the return/mean. The MEM can apply the same approach to minimize the market price uncertainty and maximize the return, which in the MEMs case is to minimize the expected TOC. The objective function is formulated as shown below:

$$\min \sum_{t=1}^{T} \left[r\left(\left[P_{grid} \right]^T \left[\Sigma_{DA-RT} \right] \left[P_{grid} \right] \right) + m\left(\left[P_{grid} \right] \left[Mean \right]^T \right) \right]$$

P_{grid} is the power to be purchased from the day-ahead and real-time market. The covariance matrix Σ_{DA-RT} or the variance in the market prices, is calculated using the approach mentioned in the following section and the mean is simply the expected market price. The idea behind variance as a measure of risk is that the variance measures the volatility. The more a stock's returns vary from the average return, the more volatile is the stock. Markowitz optimization framework uses variance to quantify risk under the assumption that the market prices follow Gaussian distribution. A limitation to use variance as a measure of risk is that it adds weights to the numbers since variance is the average of the squared differences from the mean. Weighting factors 'r' and 'm' are included to analyze the importance of risk and mean in the optimization problem. It gives flexibility to the MEM on choosing the set of optimal mix of portfolio to be invested in the day-ahead and real-time markets.

2.2. FORMULATION OF RISK/VARIANCE

The MEM tries to minimize the risk associated from both the day-ahead and the real-time markets. As discussed in the first section, the hourly prices within a market are correlated, as well as between different markets. The covariance or the risk associated with the market price uncertainty is calculated using the standard formula used for variance as shown in equation below.

$$C = E\left[(X - Mean)\,(X - Mean)^T \right]$$

X is the random vector, where $X \in R^n$. The problem is solved for a time period for 24 hours. We are calculating the variance of hourly prices within the same market, as well between both the markets. Considering each random variable to be the hourly price of the day-ahead and real-time market, n would be 48 random variables.

$$X = [X_{DA\_1}, X_{DA\_2} \ldots X_{DA\_24}, X_{RT\_1}, X_{RT\_2} \ldots . X_{RT\_24}] \quad (1)$$

Assuming that the hourly day-ahead and the real-time market prices have a Gaussian distribution, the covariance matrix is constructed. The resulting covariance matrix would be an n x n matrix and is positive semidefinite by nature.
The (i, j) th term of the covariance matrix is given by:

$$C_{ij} = E[(X_i - Mean_i)(X_j - Mean_j)] = \sigma_{ij}{}^2$$

The diagonal entries of the covariance matrix are the self-variances and are given by:

$$C_{ii} = E[(X_i - Mean_i)^2] = \sigma_i{}^2$$

The risk/covariance factor thus looks like:

$$\Sigma_{DA-RT} = \begin{bmatrix} \sigma^2{}_{DA} & \sigma^2{}_{DA-RT} \\ \sigma^2{}_{DA-RT} & \sigma^2{}_{RT} \end{bmatrix}$$

2.3. ENERGY SCHEDULING PROBLEM

The objective function for the energy scheduling problem must contain both the mean/variance of the market purchase cost as well as the expected TOC to be minimized. Hence, the cost associated with operating the various DERs and energy storage is added to the objective function.

$$\min \sum_{t=1}^{T} \left[r\left(\left[P_{grid} \right]^{T} \left[\Sigma_{DA-RT} \right] \left[P_{grid} \right] \right) + m\left(\left[P_{grid} \right] \left[Mean \right]^{T} \right) + \sum_{i=1}^{n} C_{Gi} P_i(t) \right] \quad (2)$$

The various constraints for this problem are as follows:

$$P_{grid}(t) + \sum_{i=1}^{n} P_i(t) = P_D(t) \quad (3)$$

$$E_i(t+1) = E_i(t) \ + \ P_i(t)\eta\Delta t \quad i \in s, \forall t \quad (4)$$

$$P_{grid,\min} \le P_{grid}(t) \le P_{grid,\max} \quad (5)$$

$$P_{i,\min} \le P_i(t) \le P_{i,\max} \quad (6)$$

$$U_i(t) P_{i\min}^{+} \le P_i^{+}(t) \le U_i(t) P_{i\max}^{+} \quad i \in s, \forall t \quad (7)$$

$$(1-U_i(t)) P_{i\min}^{-} \le P_i^{-}(t) \le (1-U_i(t)) P_{i\max}^{-} \quad i \in s, \forall t \quad (8)$$

$$U_i(t) \rightarrow \text{binary variable}$$

The constraints have been developed for a similar problem in one of our previous works [13]. The decision variables are P_{grid}, P_i, P_i^+, P_i^-, E_i and U_i for $i \in s$ where s denotes the energy storage components. C_{Gi} is the (\$/MWh) cost for the DERs and energy storage. The supply demand balance constraint is shown in equation (3). The sum of the energy purchased from the grid and the aggregated sum of the DERs and energy storage must meet the load at a given time period. The proposed method is shown in the form of a diagram in Figure 2.1.

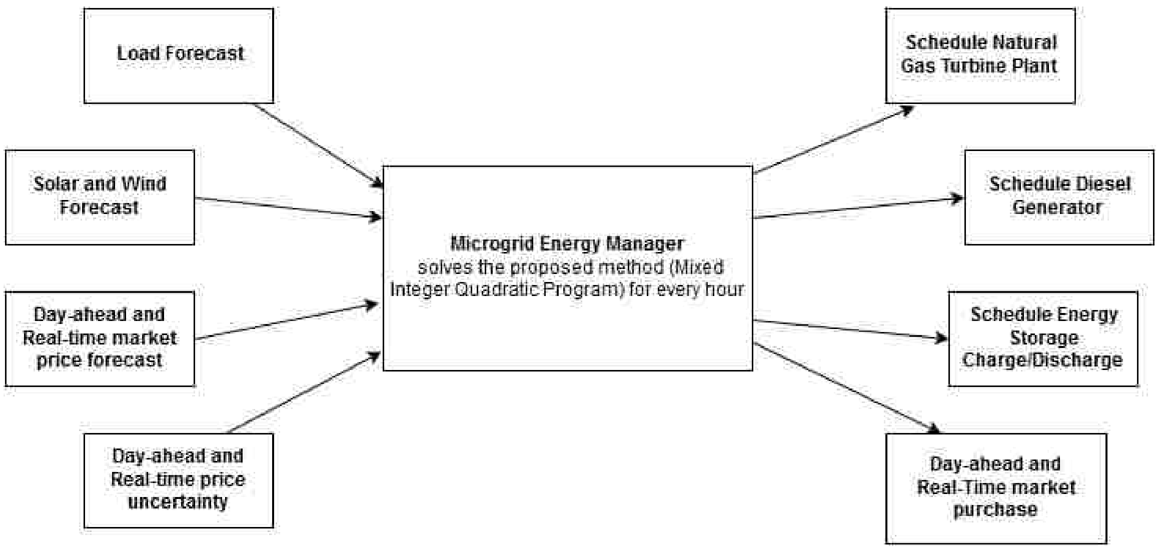

Figure 2.1. Problem solved by the MEM

The energy stored at a given period is shown in equation (4), where η is the efficiency of the energy storage system. Equations (5) and (6) are the bounds on grid purchase power and distributed generations. The reason for including an integer variable (U) is because the energy storage system can either charge or discharge at any given moment. It is also important to note that the storage could be in an idle state and U could take the value of either 0 or 1.

The MEM solves the mixed integer quadratic program for every hour to schedule the DERs and purchase power from both the markets. The load forecast, solar and wind forecast, day-ahead and real-time market price forecast and the day-ahead and real-time price uncertainty are obtained for every hour. The result of this problem gives the energy to be scheduled by the DERs as well as the power to be purchased from the both the day-ahead and real-time market to meet the microgrid demand.

3. NUMERICAL EXAMPLE AND SIMULATION RESULTS

3.1. THE MICROGRID AT ILLINOIS INSTITUTE OF TECHNOLOGY

To verify the proposed method with a numerical example, we consider the microgrid at the Illinois Institute of Technology (IIT) in Chicago, Illinois. The system consists of solar, wind, natural gas turbine power plant, a flow battery energy storage system and multiple backup generators to meet a peak load of roughly 13MW [14]. With multiple objectives such as reduced energy costs, improvement of reliability and quality and reduction of CO_2 emissions, the system at IIT is chosen as a case study for validating the proposed model. The capacities of the DERs and their per-MWh production costs are given in Table 3.1. The $/MWh for natural gas and diesel for natural gas turbine power plant and backup generators respectively were obtained from the U.S Energy Information Administration [15 - 16]. The $/MWh for the flow battery storage was obtained from [17].

Table 3.1. Distributed energy resources of the microgrid at IIT

Technology	Total output capacity (MW)	Total MWh capacity	Production cost ($/MWh)
Solar	0.300		
Wind	0.008		
Natural Gas Turbine	8.000		22.987
Flow Battery Storage	0.250	0.500	108
Backup Generators	4.036		66.584

The hourly load data for Microgrid at IIT is shown in the plot below. The peak load is around 12.9 MW as shown in Figure 3.1. The load profile follows a regular commercial load profile pattern where the peak is around 15th hour and falls back eventually towards the end of the day. It is evident that when there is a grid outage, roughly 60% of the load is powered by the natural gas turbine power plant and the reason is clear due to the $/MWh price of natural gas.

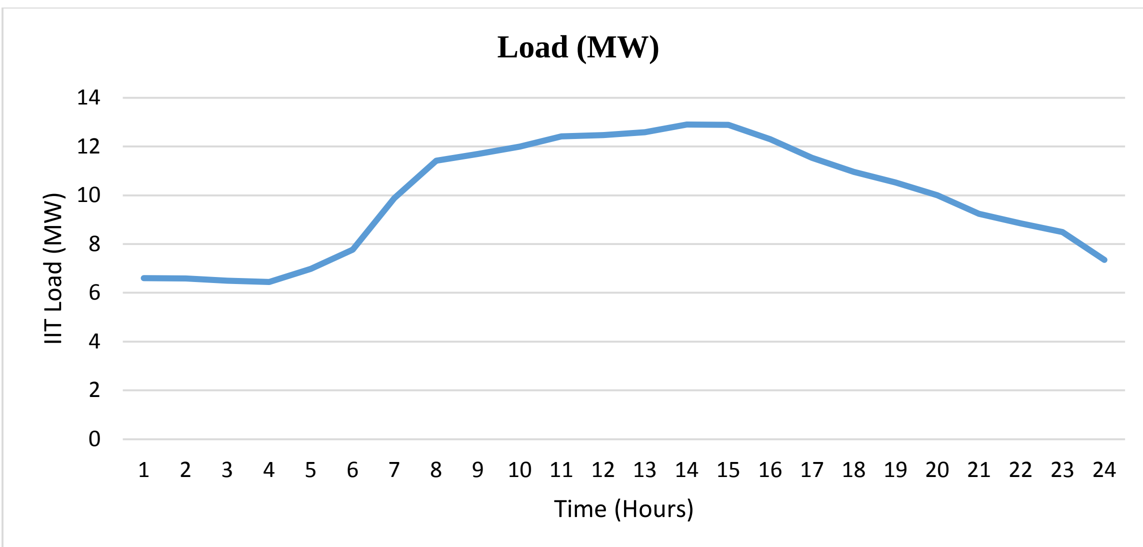

Figure 3.1. Load profile of microgrid at IIT

3.2. COVARIANCE OF PJM'S DAY-AHEAD AND REAL-TIME MARKET PRICES

The problem is solved using data recorded during the summer of 2015. The day-ahead and real-time market prices were taken from PJM, as the IIT microgrid is located under the operation of PJM. To construct the covariance matrix, the day-ahead and real-time market prices of 92 days, from beginning of June to the end of August were downloaded from the PJM data miner [18].

The heat map of the covariance matrix is shown in Figure 3.2. The heat map shows the volatility of the hourly market prices and this information can be used to minimize the variance of the market purchase cost. The real-time market is highly uncertain as it is cleared post demand and is used to meet the difference between the forecasted and actual demand. The day-ahead and real-time market prices are assumed to have a Gaussian distribution. The covariance matrix is semi-positive definite and symmetric by definition.

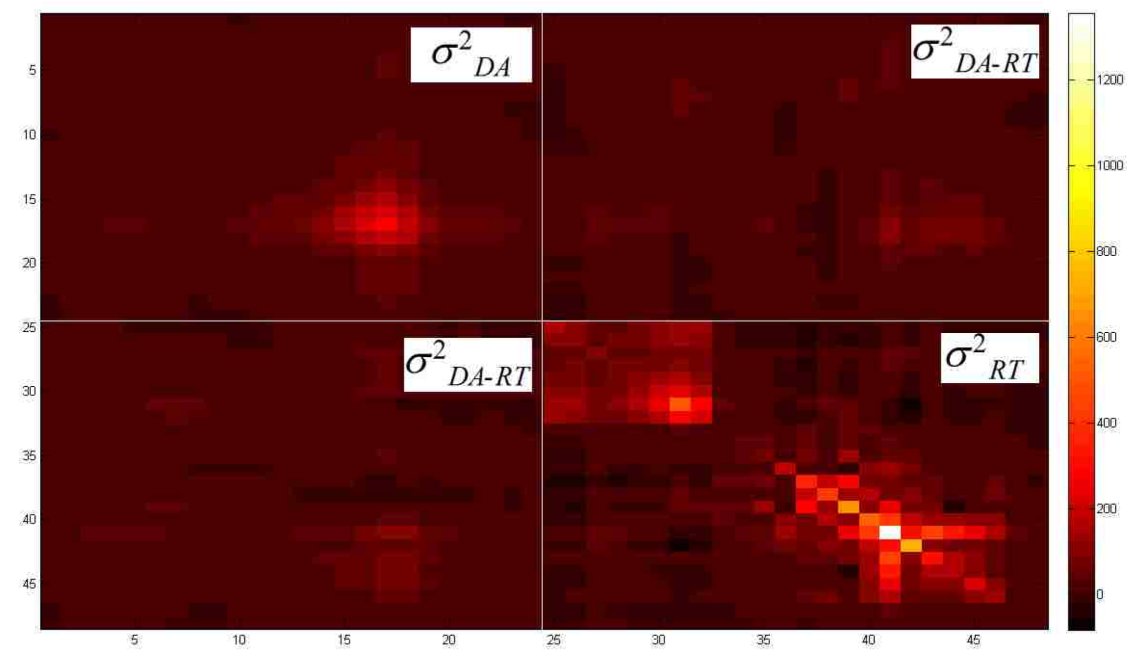

Figure 3.2. Heat Map of Covariance Matrix

3.3. SOLAR AND WIND PRODUCTION DATA

The hourly solar PV output data was obtained using NREL PVWatts Calculator [19]. With inputs as the location, the system size (kW-DC) and other parameters such as system losses, array type, etc., it estimates the energy production of solar PV systems, which in our case was Chicago, IL. The data is obtained for 1kW of capacity and scaled up to the capacity of microgrid at IIT, which is 300 kW. Figure 3.3 shows the solar and wind production data simulated using the PV Watts calculator and the wind energy production calculated from the above method respectively for 24 hours.

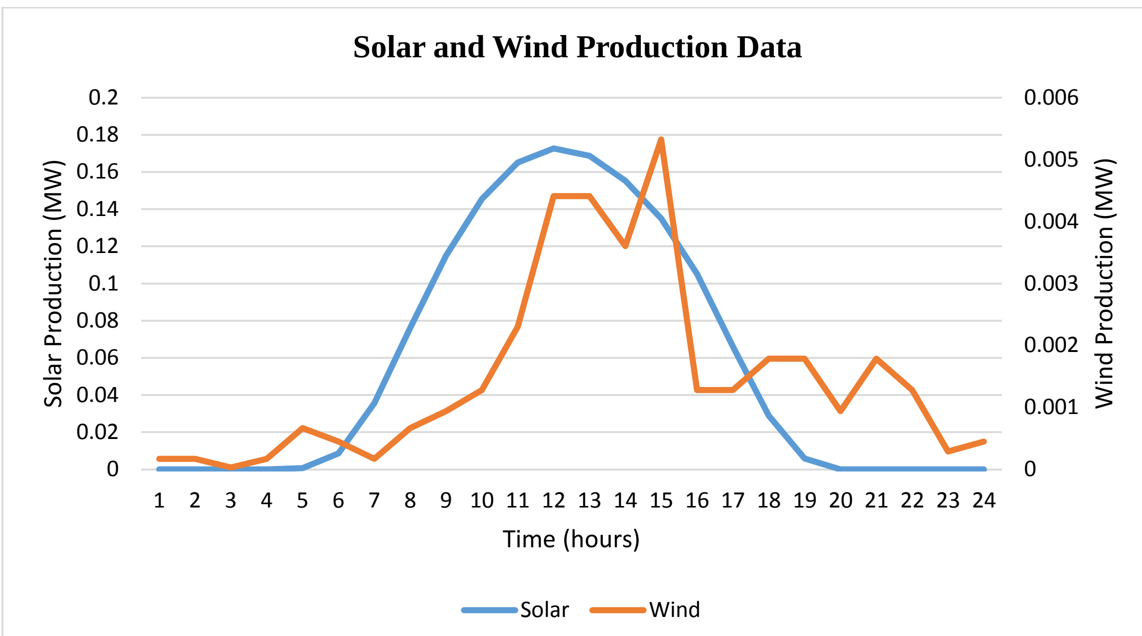

Figure 3.3. Solar and wind output in Chicago, Illinois

Wind energy production depends on factors such as the turbine length, wind speed, air density and the Albert Betz coefficient. The wind speed data was obtained from

NREL Renewable Resource data center for Chicago [20]. Wind power was calculated as follows:

$$\text{Wind Power (kW)} = \frac{1}{2}\rho A v^3 C_p$$

ρ is the air density (1.23 kg/m^3), A is the area swept by the blade (m^2), and v is the wind speed (m/s), and C_p is the Betz limit coefficient (generally between 0.35 and 0.45).

3.4. THE PROBLEM OF ENERGY SCHEDULING

The mixed integer quadratic program formulated in Section 2.3 is solved using OPTI TOOLBOX [21] with MATLAB interface. [21] can be used to solve linear, nonlinear, continuous and discrete optimization problems using MATLAB. The problem is solved for 24 hours in an hourly interval.

The simulation was run initially for variance scaling factor r=1 and mean scaling factor m=1 in Equation (2). The result of this optimization problem gives the schedule of optimal DER operation and the energy to be purchased from the day-ahead and real-time markets.

The expected TOC of the microgrid was found to be $7,399.3. This cost includes the cost of operation of the DERs as well as the market purchase cost to meet the microgrid load for 24 hours. The mean of the purchase cost from the wholesale electricity market was found to be $184.65 with a variance of purchase cost of 283.55.

In order to provide a better picture of the results, Figure 3.4 provides the schedule of the DERs and the microgrid demand. It is clear that during the peak demand of the day, the natural gas turbine plant and diesel generator are being operated to their full capacities. In fact, the cost of operating the natural gas turbine plant and diesel generator combined was found to be $7,214.6 which is 97.5% of the TOC of the microgrid.

This is because of the inclusion of the risk factor (covariance of market prices) in the objective function due to which the market purchase/sale schedule are limited accordingly. The level of importance given to the risk in the objective function is decided by the MEM.

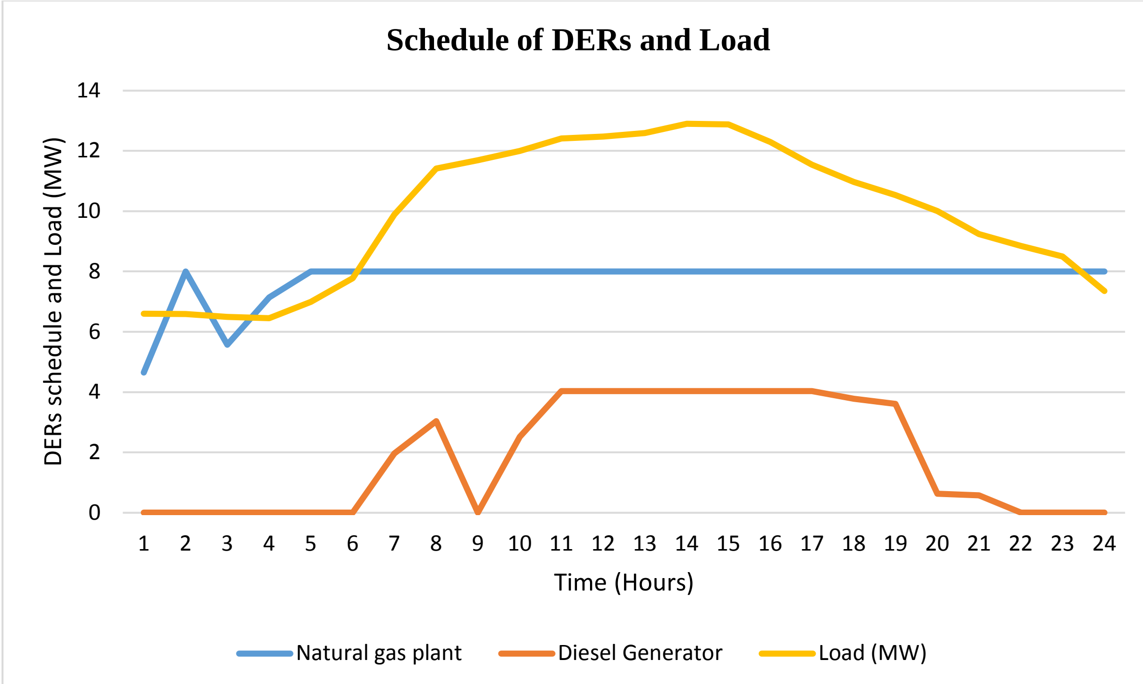

Figure 3.4. Schedule of the DERs and Load

As the level of importance for risk changes, the schedule of market purchase/sale changes accordingly, which in turn has an effect on the operating schedule of DERs as well. This is discussed more in the next section. Figure 3.5 represents the schedule of energy storage. The positive schedule is the charging and the negative schedule is the discharging of the energy storage.

Figure 3.6 shows the schedule of the market purchase/sale. Based on the expected market prices and covariance of market prices, the day-ahead and real-time market purchase/sale is scheduled by the MEM for every hour. The day-ahead purchase at hour 9 and 10 is higher because of the risk (covariance) being comparatively lower for that period. This can be verified using the covariance matrix of the hourly market prices. Also, it is important to note that the purchase/sale from real-time market is not as active as day-ahead market. This is because of the fact that real-time market prices are more uncertain than the day-ahead markets. It makes sense because the real-time markets are designed to meet the difference in the forecast and actual demand of the system operator and is cleared every 5 minutes after the actual demand of the system.

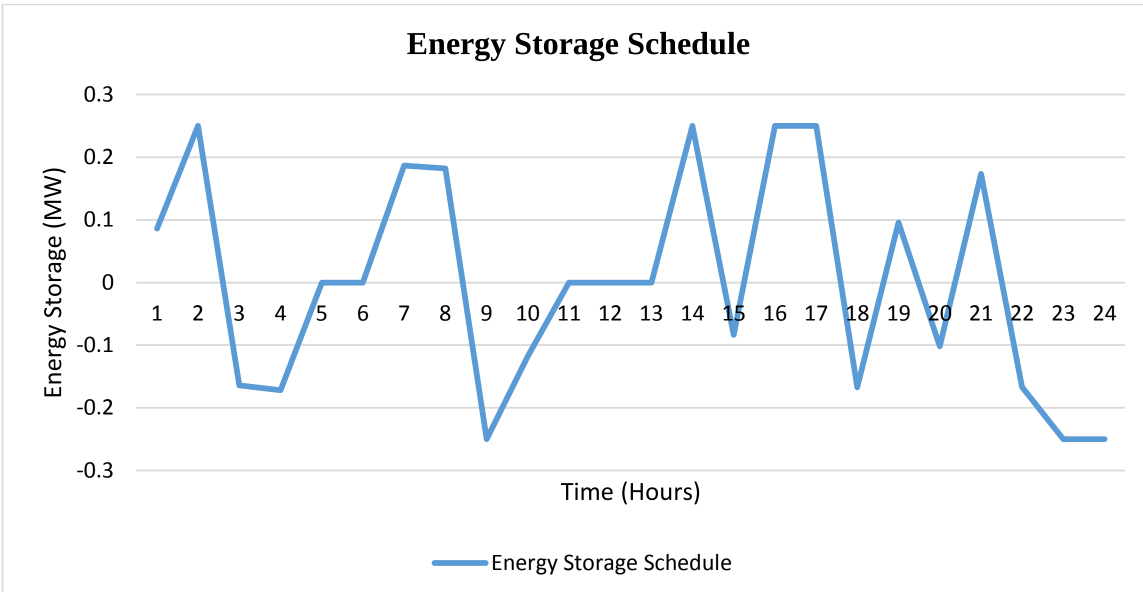

Figure 3.5. Schedule of Energy Storage

Thus the MEM limits the trading activity in real-time markets to avoid the risk of market price uncertainty.

As mentioned before, the total market purchase cost was found to be $184.65. This cost comprises of the day-ahead market purchase cost ($390.676), day-ahead market sale revenue ($153.33), real-time market purchase cost ($78.63) and real-time market sale revenue ($131.33). The MWh energy trading (purchase/sale) by the MEM in both the markets for 24 hours combined (over a day) is shown in Figure 3.7. It is pretty evident that the significance of Figure 3.2 has a direct impact on the market trading of the MEM.

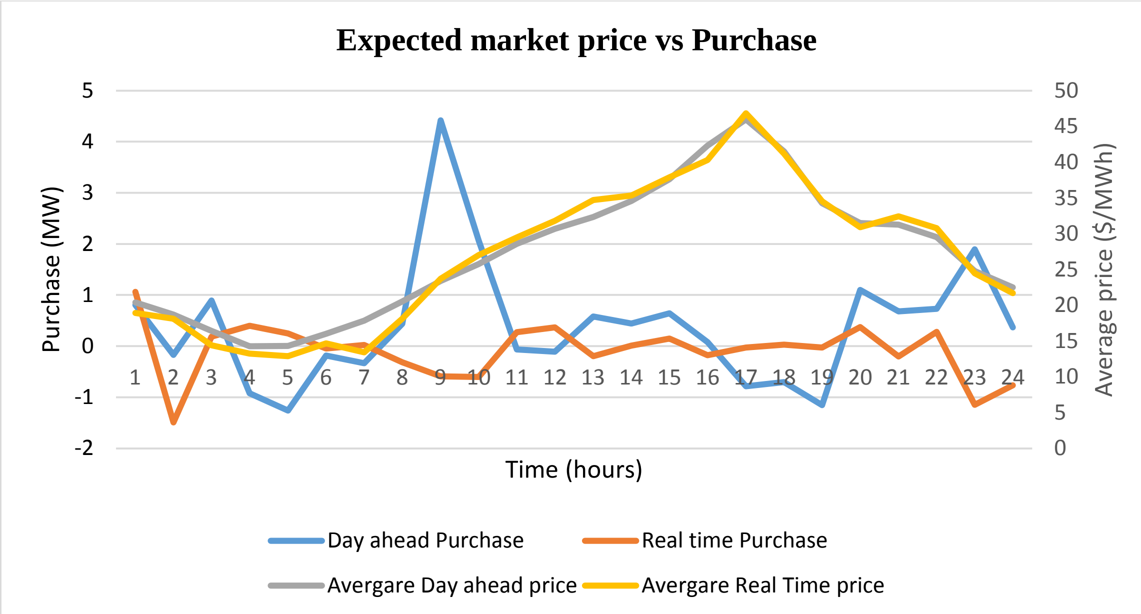

Figure 3.6. Expected market price vs Purchase from the markets

To analyze the impacts of the risk factors in operation decisions, the scaling factors are varied to see how the scheduling of DERs and market purchase varies accordingly.

It is important to note that the purchase from the market and the scheduling the DERs are complimentary to each other, since the cost of purchasing energy from markets is cheaper than operating the DERs to meet the load. That is, when there is more energy purchased from the market to meet the load, the expected TOC becomes less and vice versa. This leads to the important analysis of this work.

The tradeoff between the risk and return, which in the MEMs case is the tradeoff between risk/uncertainty of the market price and expected TOC is analyzed. Another important part of the analysis is to see whether assuming that market prices follow a Gaussian distribution is reasonable or not.

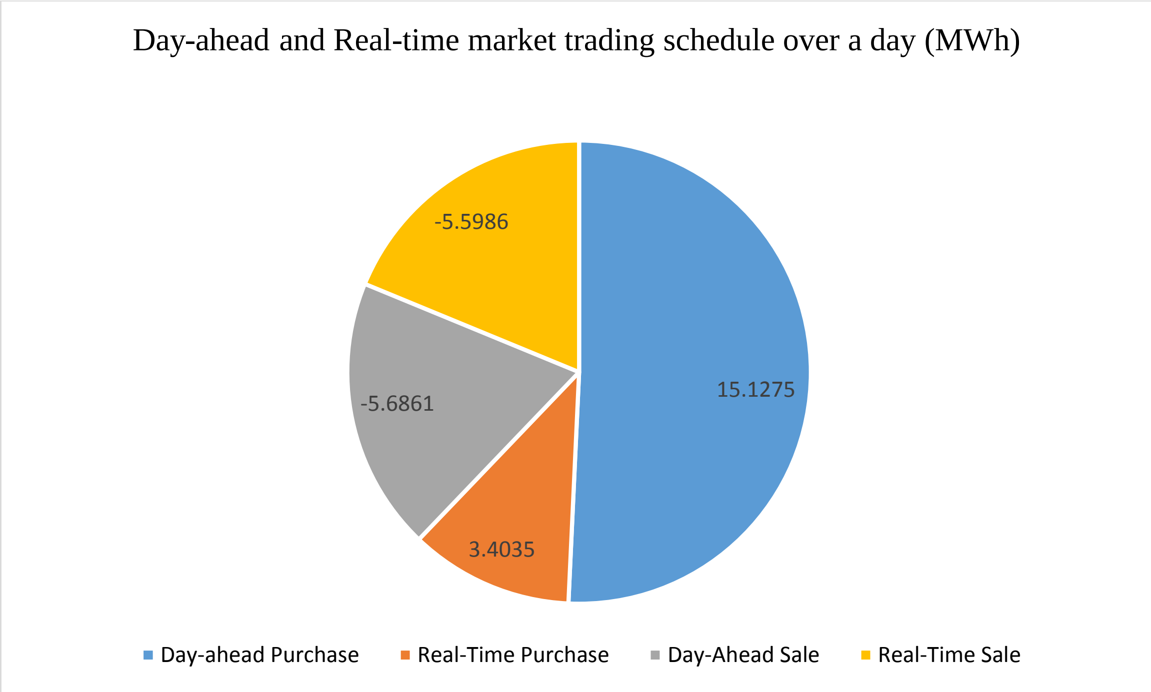

Figure 3.7. Day-ahead and real-time trading (MWh)

3.5. RISK AND EXPECTED TOC TRADEOFF

The tradeoff faced by the MEM with uncertain prices is the willingness to take higher risks, which could possibly yield higher returns but at a low probability. In order to analyze the tradeoff between the risk/variance of the market purchase cost and expected TOC of the microgrid, the scaling factors ‘r’ and ‘m’ in Equation (2) are varied. This leads to the 2 modes of operation by the MEM, the risk-averse and the risk-taker mode. The tradeoff is depicted in Figure 3.8.

Placing a higher weight of minimizing the risk in the objective function decreases the variance of the market purchase cost. In this case, the MEM is concerned more about the uncertainty of the market purchase cost and hence is willing to operate the DERs more instead of purchasing from the market.

Therefore, the expected TOC increases due to the increased operation of DERs and less purchase from the market. This is the risk-averse mode of the MEM.

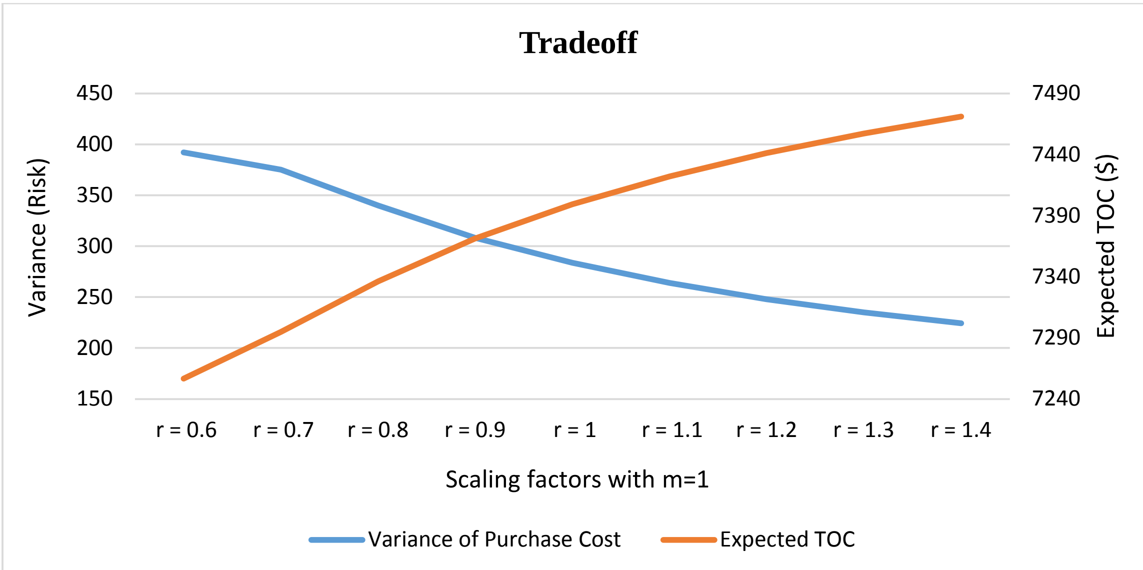

Figure 3.8. Tradeoff between risk and expected TOC

On the other hand, when the weight of the risk component is decreased in the objective function, the variance of the market purchase cost increases having a direct impact on usage of the DERs accordingly. This is the risk-averse mode of the MEM. The cost of operating the DERs decreases since most of the energy needed to meet the demand are purchased from the grid which is cheaper than the operating cost of DERs, thereby decreasing the expected TOC. When substituting r = 0.6 and m =1 in Equation 2, the variance of the purchase cost was found to be 391.97 and the expected TOC to be $7,256.7. Hence it is evident that when the variance of the purchase cost increases, the expected TOC decreases and vice versa. Table 3.2 below gives the comparison between the operation of the risk-averse MEM and risk-taker MEM.

Table 3.2. Distributed energy resources of the microgrid at IIT

Risk-Averse MEM (r = 1.4)	**Risk-Taker MEM (r = 0.6)**
Variance (Risk) of Purchase Cost: 224.38	Variance (Risk) of Purchase Cost: 391.97
Expected Market Purchase Cost: $140.33	Expected Market Purchase Cost: $267.23
Operating Cost of DERs/Storage: $7330.8	Operating Cost of DERs/Storage: $6989.5
Expected TOC: $7471.2	Expected TOC: $7256.7

Figure 3.9 compares the market purchase activity of risk-averse MEM and risk-taker MEM. The MEM as risk-taker purchases more power from the market as compared to the risk-averse MEM, i.e. willing to take higher risks, which could possibly yield higher returns but at a low probability. Once again, the day-ahead purchase is more than the real-time due to the higher uncertainty or risk involved with real-time markets.

Figure 3.10 compares the operation of DERs of a risk-averse MEM and a risk-taker MEM. The risk-averse MEM operates the DER more when compared to the risk-taker MEM, in order to avoid the risk of market price uncertainty. This increases the expected TOC of the microgrid but it is more certain to happen as the risk involved with respect to the market purchase is lower.

With this information, the MEM can now make decisions in the day-ahead and real-time markets according to their risk aversion preference. It is once again important to note that the decision of their risk aversion preference has an impact on the market trading activity, which in turn can change the schedule of operation of DERs accordingly, thereby having an effect on the expected TOC of the microgrid. For example, if the MEM prefers to reduce the operation of the DERs and bring down the expected TOC of the microgrid, the tradeoff information can give the MEM the risk involved to achieve the desired result.

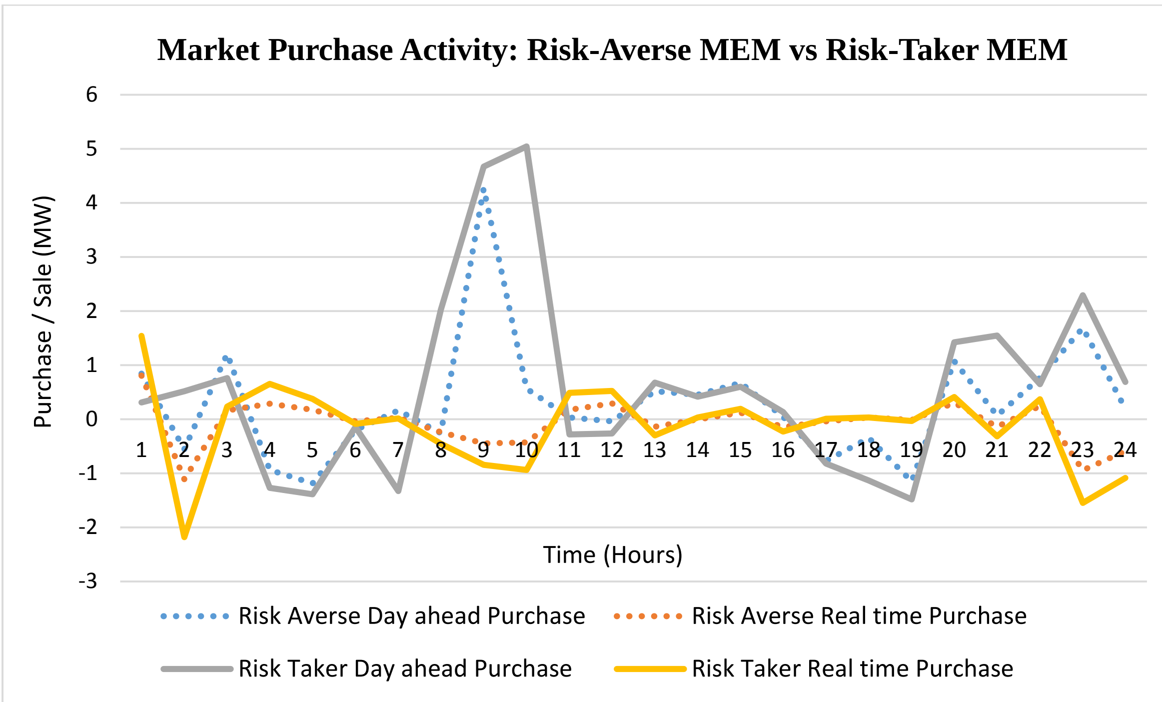

Figure 3.9. Market purchase activity of a Risk-Averse MEM vs Risk-Taker MEM

3.6. VERIFYING THE GAUSSIAN DISTRIBUTION ASSUMPTION OF THE MARKET PRICES

The second part of the analysis is to check whether assuming the market prices to be normally distributed is reasonable. The hourly market prices that were used to construct the covariance matrix/risk associated were assumed to follow a Gaussian distribution in order to apply the Markowitz optimization theory.

But in reality, the market prices do not follow a Gaussian distribution. Figure 3.11 shows the histogram plot of day-ahead market price for hour 1. It is evident that the prices do not follow the distribution that we had assumed for simulating the proposed method.

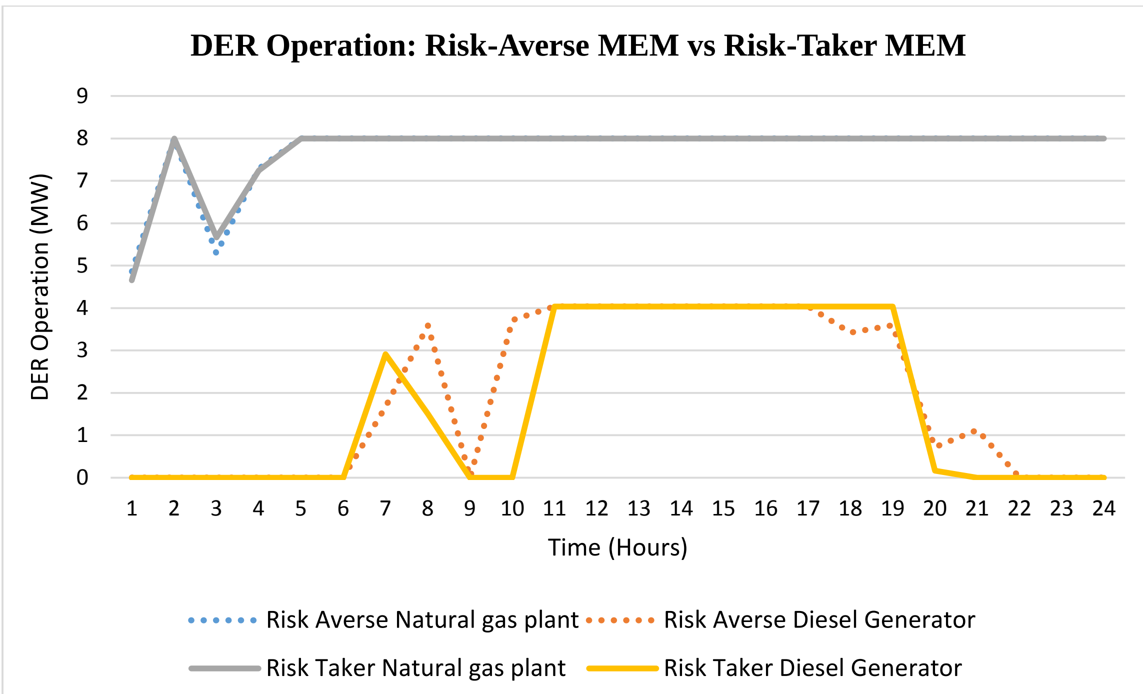

Figure 3.10. DER operation of a Risk-Averse MEM vs Risk-Taker MEM

To verify the Gaussian distribution assumption, a sample of 1,000 market prices for each hour, both for the day-ahead and the real-time markets were generated. This is done by randomly generating samples using the distribution of actual historic market price data [9].

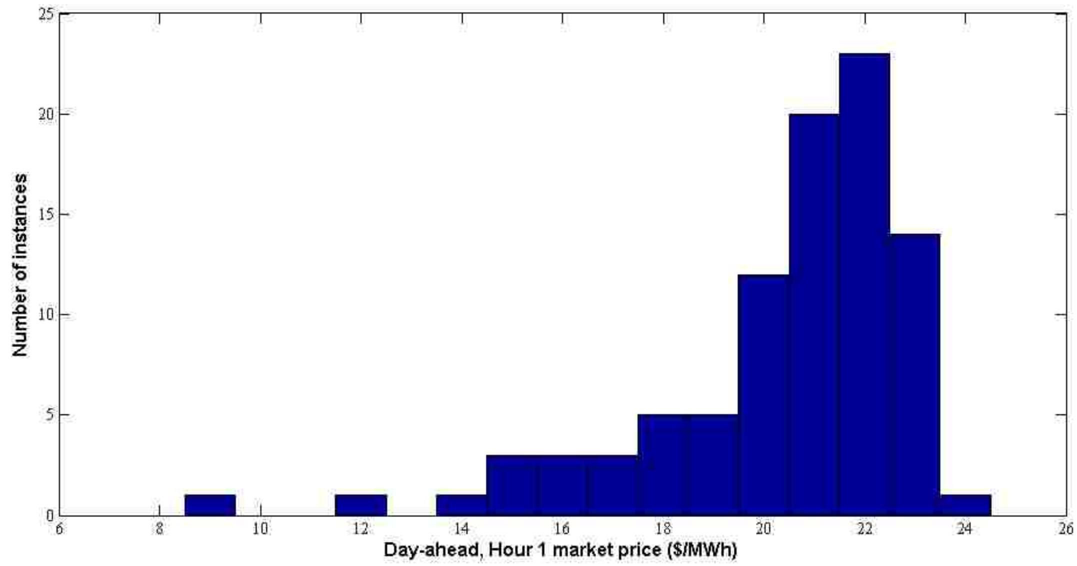

Figure 3.11. Distribution of day-ahead, hour 1 market prices

To check if the assumption was a reasonable one, we intend to compare (a) the expected TOC obtained with the assumption of market prices following Gaussian distribution and (b) expected TOC with the generated sample market prices that follow the distribution of actual historic market price data.

Hence, the purchase/sale portfolio obtained as a result of solving the proposed mixed integer quadratic program is used to calculate (a) and (b), the only difference being for that of (b), we use the generated sample market prices. The histogram plot of (b) is shown in Figure 3.12.

It is evident that (a) and mean of (b) are almost equal. (a) was found to be $7399.3 in Section 3.4 and the mean of (b) was found to be $7394.9. This proves that the assumption of market prices following Gaussian distribution is a reasonable one for the purpose of hedging against the risks and also validates the method of applying Markowitz optimization to find the optimal set of purchase/sale portfolio in the day-ahead and real-time markets. It also gives flexibility to the MEM for making decisions in the day-ahead and real-time markets according to their risk aversion preference.

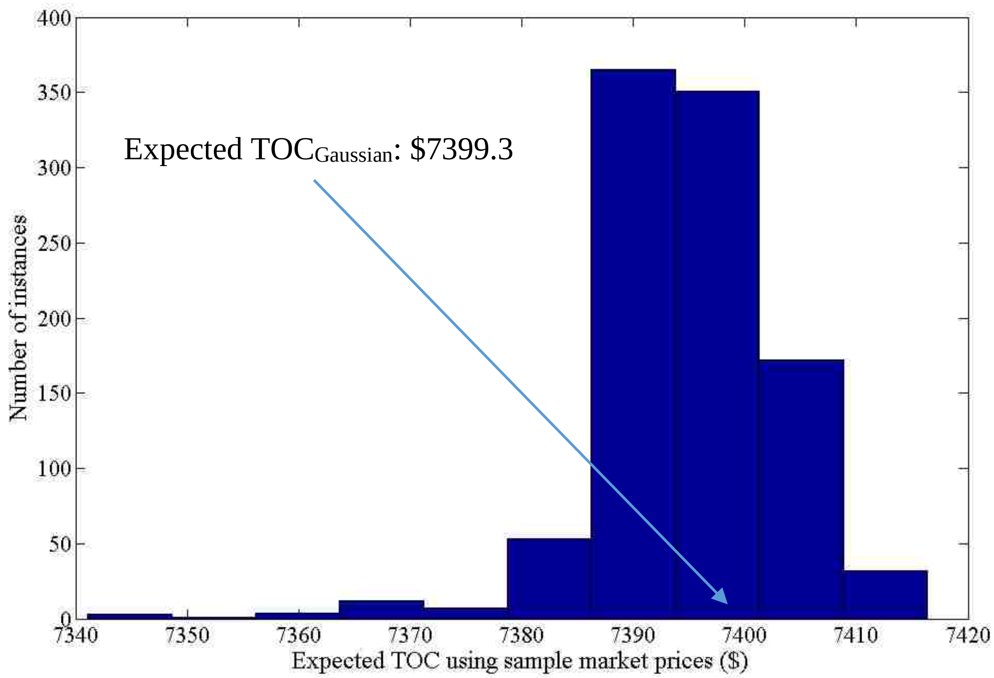

Figure 3.12. Validating the assumption of market prices following Gaussian distribution

4. CONCLUSION

In this work, the problem of a MEM has been solved to schedule the energy resources and storage to meet the load of the microgrid. The idea of microgrid as an individual market player in the wholesale electricity market has been explored. The day-ahead and real-time market price uncertainty has been taken into account while solving the energy scheduling problem and a risk management method is proposed for the same. Simulation results show that the risk is minimized and there is generally a tradeoff between the variance/risk of the purchase cost and the expected TOC of a microgrid. An important assumption of market prices following Gaussian distribution has been verified, thus validating the proposed model.

This work can be extended to include demand side management in the microgrid and see the impact of the scheduling of DERs and energy storage as well as the purchase of energy from both the markets. Another important extension of this work would to manage the uncertainty of the renewable energy resource energy production as well as the load forecast uncertainty due to the implementation of demand side management when included in the problem. Also, in order to assess the impact of risk management with better accuracy, solar, wind and load data can be obtained for a longer time period and the case study of microgrid at IIT can be simulated for multiple days and seasons.

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