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Day-Ahead Electricity Price Forecasting and Scheduling of Energy Storage in LMP Market

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ABSTRACT This paper proposes an optimization strategy for the day-ahead planning of utility owned energy storage operation while considering the electricity price volatility in locational marginal pricing (LMP) market. The proposed optimization strategy works upon the predicted day-ahead electricity prices while considering the consequences of energy storage scheduling on the next day's electricity prices. In this study, a piecewise linear relation between load and LMP is established using historical load and LMP data. The piecewise linear relation results are provided to the next stage for the proposed energy storage optimization which is solved using Quadratic Programming. This study is performed using the real historical data from New York Independent System Operator which provides price-based demand response program including day-ahead dynamic pricing which is suitable for the proposed study. The simulation is carried out for two energy storage sizes. The simulation result of our proposed optimization strategy, considering impact of energy storage charging/discharging on LMP, was compared with the optimization result considering no impact of energy storage on LMP. The results show that the proposed optimization strategy not only increases the revenue for the utility but also helps in smoothing the next day's electricity price curve.

INDEX TERMS Deregulated electricity market, energy storage, locational marginal price (LMP), price arbitrage, quadratic programming.

I. INTRODUCTION

Interest in energy storage has increased in the last few years with the rapid development of renewable energy resources which need storage to accommodate the variable nature of these new resources. Although some energy storage technologies are mature and ready to serve, many other energy storage technologies span the range of development maturity with rapid improvements in many technologies underway [1], [2]. Among all energy storage technologies, pumped hydro storage is the most mature and prevalent technology with 129 GW of installed storage capacity worldwide. Pumped hydro storage has a long economic life span (typically more than 50 years), low O&M and lack of cycling degradation. Due to high levels of wind and solar energy penetration, the need for rapid generation ramping, balancing services and moving energy from times of excess to times of high demand are expected to increase as well. Moreover, the huge differences between peak and valley loads are pushing the power companies to upgrade the existing power systems and to develop demand response (DR) programs.

There is a wide range of DR techniques such as voluntary load management programs and direct load control. However, dynamic pricing is known as one of the most common tools that can encourage users to consume wisely and more efficiently [3], [4]. In day-ahead dynamic pricing, users may adjust power demand by postponing some tasks that require large amounts of electric power, or may decide to pay a higher price for their electricity. One of the most promising dynamic pricing schemes is Locational Marginal Price (LMP) [5]. LMP is the marginal cost of supplying the next increment of electric demand at a specific location (node) on the electric power network, taking into account supply bids, load demands and the physical aspects of the transmission system including transmission and other operational constraints [6], [7]. Therefore, LMP represents the overall grid status as these prices include the basic electricity generation costs, transmission losses and increase in costs due to transmission network congestions. Due to LMP's localized pricing strategy, the charge/discharge cycles of utility owned large scale energy storage would consequently impact the load demands

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and thus electricity prices. Therefore, LMP's high volatility of electricity prices has been a significant concern for utility owned energy storage as it bears significant financial risks.

Some studies have investigated the ways to optimize the energy storage using day-ahead pricing and have provided impressive results. A profit maximizing approach for investment planning of energy storage systems which ensure that the owner of the energy storage will maximize its benefits has been proposed in [8], [9]. Whereas in [10], the potential of energy storage is compared with the DR strategies for electricity cost reduction in the residential sector and the benefits of energy storage and demand response are evaluated through an optimization analysis with a linear programming algorithm. The results suggest a significant decrease in the battery prices can make storage an interesting alternative, especially for the cases in which demand response is not easily applicable. With decreasing battery prices, plug-in hybrid electric vehicles can become valuable resources for electric grid by providing vehicle to grid services [11]–[13]. In [14], a bi-level energy storage arbitrage model is proposed in which the energy storage arbitrage revenue is maximized while considering wind power effect on the market clearing process. The proposed model is expressed as a mathematical program with equilibrium constraints (MPEC) and then reorganized in the form of mixed integer linear programming (MILP) using strong duality theory. In [15], energy storage is used to reduce electrical system congestion by sending cost-reflective signals to energy storage in order to affect its operation in responding to network conditions. The authors designed a new energy storage charging and discharging strategy based on Binary Search Method (BSM). In [16], a risk constrained energy storage scheduling technique for the electrical utility company is proposed in which the uncertainty of demand and price are considered. Their results demonstrate that considering the risk in energy storage scheduling model can significantly change the utility's expected profit. In [17], the impact of DR has been studied on the LMP while considering transmission network congestions. The authors formulated and solved this network constrained social welfare optimization problem as MILP which includes the revenue from DR loads minus the energy production costs.

The DR and effectiveness of energy storage in the smart grid has been addressed and optimization strategies have been proposed in the above mentioned studies. Recently, few authors have addressed the usefulness of their studies if their energy storage optimization technique makes an impact on the price curve. It is believed that as the penetration of large scale energy storage and DR increases, it will increase the smoothness of the electricity price curve. And as the electricity prices are getting more localized with the adoption of LMP by the electrical system operators, the impact can get significant.

The utility's revenue from the energy storage is a function of both net load demand and wholesale electricity prices. Whereas, electricity load and price are strongly correlated in LMP market. Price changes due to large storage charging and discharging will cause an amplified effect on the utility's revenue. In order to solve this optimization problem of two highly correlated independent variables, in this study, a Quadratic Programming [18] based optimization strategy is proposed for the day-ahead planning of energy storage operation while considering the price volatility. The objective is to maximize the revenue for the utility owned energy storage. We compare our results with different sizes of energy storage with the optimization strategy as proposed in former studies which have not considered impact of energy storage on electricity price. In the end, we analyze the variation in the price curve due to the charging and discharging of energy storage. Results validate that the proposed optimization strategy not only increases the revenue for the utility but also helps in the smoothing of the day-ahead price curve.

The proposed solution works upon the predicted day-ahead electricity price curve while considering the fact that the outcome of energy storage scheduling will affect the predicted price curve. Thus as a sub-part of this study, we forecast day-ahead electricity price with the use of previously forecasted load. Various electricity load and price forecasting techniques are discussed in [19], [20]. Among many forecasting techniques, artificial neural network has emerged as one of the most prominent technique [21]. In this study, we forecast day-ahead LMP based on Artificial Neural Network [22] and establish a relation between load and LMP using piecewise linear regression [23]. These results are provided to our proposed solution as inputs to optimize the energy storage scheduling.

The remainder of this paper is organized as follows. Section II explains the overall structure of a deregulated electricity market and how electricity prices are determined for the following day. Section III introduces the system model of proposed quadratic programming based optimization for energy storage along with the price forecasting model. Section IV demonstrates the simulation results to clearly verify the proposed strategy. Whereas, Section V concludes the study.

II. DEREGULATED ELECTRICITY MARKET

The day-ahead market is the main arena for trading power. Here, contracts are made between seller and buyer for the delivery of power for the following day. The electricity price is determined by matching the day-ahead supply bids from the generator companies (GENCOs) with demands from the Utilities / Load Serving Entities (LSEs) to develop classic supply and demand equilibrium. In a deregulated electricity market, the price determination task is done by an Independent System Operator (ISO) which is a federally regulated independent entity established to coordinate with regional Transmission Company (TRANSCO) in a non-discriminatory manner and ensure the safety and reliability of the electricity system [24].

Various studies have shown that the utility owned integration of energy storage increases more social welfare rather than generation or consumer owned energy storage.

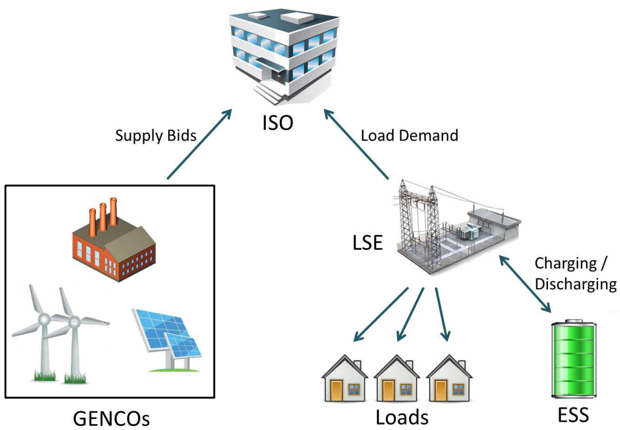

FIGURE 1. Deregulated electricity market structure.

Utility owned energy storage uniformly improves the retail profit and as the level of integration increases, the proportion of benefits goes to the consumers as well [25]–[27]. Therefore in this study, a large scale Energy Storage System (ESS) is integrated with LSE. Fig. 1 shows an overall structure of a deregulated electricity market.

III. SYSTEM MODEL

A. REVENUE MODEL OF UTILITY OWNED ENERGY STORAGE

The objective of the utility owned ESS scheduling is to maximize its net revenue for the day-ahead hourly market considering the impact of ESS on the LMP. The utility's revenue (R) from the ESS can be written as,

$$R = \sum_{t=1}^{24} \left(P_{retail,t} * E_{Sold,t} - LMP_t * E_{Pur,t}\right) \tag{1}$$

where $P_{retail,t}$ is the electricity retail price for customers at time period t and LMP_t is the locational marginal price at which the utility pays the ISO for the purchase of electricity in the wholesale market at time period t. $E_{Sold,t}$ is the amount of energy sold to the customers with the discharging of ESS whereas, $E_{Pur,t}$ is the amount of energy purchased from ISO to charge the ESS during time interval t.

For the valuation of only ESS on the utility's retail profit, we will keep the LMP_t as the retail price. Therefore,

$$R = \sum_{t=1}^{24} LMP_t \left(E_{Sold,t} - E_{Pur,t}\right) \tag{2}$$

In this process, the decision variables are the 24 hour schedules of ESS charging and discharging power which would affect the volatile LMP_t. As the load demand will increase due to ESS charging, it will incur additional charges to the price. Whereas, when the load demand is served by the ESS discharging, the market price of electricity will decrease. Therefore, it can be assumed that ΔLMP_t be the change in price due to ESS charging/discharging at time interval t. ΔLMP_t can also be expressed as the difference between the forecasted price ($LMP_{Fcst,t}$) and actual price (LMP_t).

$$LMP_t = LMP_{Fcst,t} + \Delta LMP_t \tag{3}$$

Equation (2) becomes,

$$R = \sum_{t=1}^{24} (LMP_{Fcst,t} + \Delta LMP_t) * \left(E_{Sold,t} - E_{Pur,t}\right) \tag{4}$$

The amount of electricity that can be charged ($E_{C,t}$) or discharged ($E_{D,t}$) during each time interval is limited by the charging and discharging efficiency i.e. α and β respectively. This can be expressed as,

$$E_{C,t} = E_{Pur,t} * \alpha \tag{5}$$

$$E_{D,t} = E_{Sold,t} / \beta \tag{6}$$

Therefore,

$$E_{Pur,t} = E_{C,t} / \alpha \tag{7}$$

$$E_{Sold,t} = E_{D,t} * \beta \tag{8}$$

ΔLMP_t is a function of rate of change in energy consumption (ΔE_t) at time interval t due to charging/discharging of ESS. Hence the relation between ΔLMP_t and ΔE_t can be obtained by the regression analysis in which the rate of change of energy consumption (ΔE_t) due to rate of change of price (ΔLMP_t) can be expressed by M.

$$\Delta LMP_t = M * (\pm \Delta E_t) \tag{9}$$

The energy storage charging will incur increase in the LMP_t while the discharging will decrease the LMP_t. Hence,

$$\Delta LMP_t = M(E_{C,t} - E_{D,t}) \tag{10}$$

As ΔE_t, $E_{Sold,t}$ and $E_{Pur,t}$ are the functions of decision variables i.e. $E_{C,t}$ and $E_{D,t}$. Hence the equation for utility revenue becomes,

$$R = \sum\nolimits_{t=1}^{24} (LMP_{Fcst,t} + M(E_{C,t} - E_{D,t})) * \left(E_{D,t} * \beta - E_{C,t}/\alpha\right) \tag{11}$$

It can be observed that the revenue function has a quadratic form. Therefore in this study, the optimization problem to maximize utility's revenue is solved by the quadratic programming provided with the linear constraints of energy storage.

B. LINEAR CONSTRAINTS OF ENERGY STORAGE

ESS modeling in this study consists of three kinds of constraints i.e. charging/discharging bound constraints, energy storage inequality constraints and energy storage equality constraints.

1) Charging/Discharging Bound Constraints: The quantity of electricity that can be charged ($\mathrm{E_{C,t}}$) or discharged ($\mathrm{E_{D,t}}$) during each time interval is limited

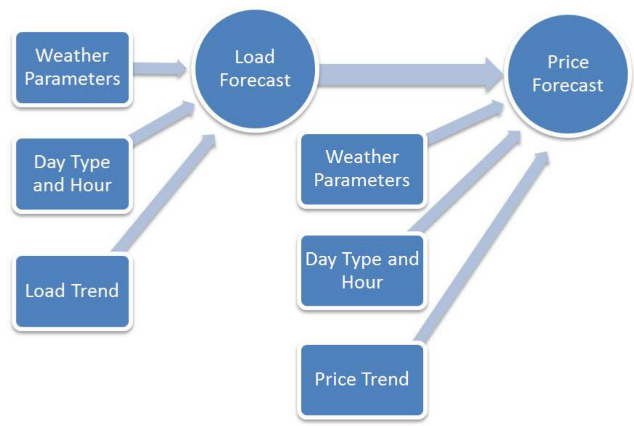

FIGURE 2. Day-ahead load and price forecast model.

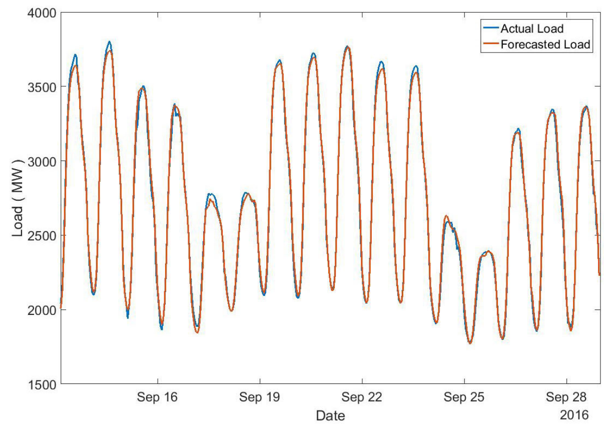

FIGURE 3. Load Forecast.

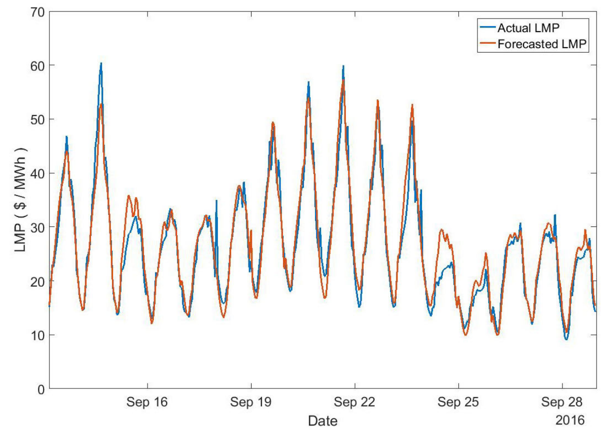

FIGURE 4. LMP Forecast.

by the maximum charging rate ($E_{C(max)}$) and maximum discharging rate ($E_{D(max)}$).

$$0 \leq E_{C,t} \leq E_{C(max)} \tag{12}$$
$$0 \leq E_{D,t} \leq E_{D(max)} \tag{13}$$

2) Energy Storage Inequality Constraints: At any time instance, the quantity of stored energy ($E_{S,t}$) i.e. the sum of all energy storage charging/discharging and the quantity of stored energy at start of the day ($E_{S(start)}$) cannot exceed maximum storage capacity ($E_{S(max)}$) or minimum storage capacity ($E_{S(min)}$).

$$E_{S,t} = \sum_{1}^{t} \left(E_{C,t} - E_{D,t} + E_{S(start)}\right) \tag{14}$$
$$E_{S(min)} \leq E_{S,t} \leq E_{S(max)} \tag{15}$$

3) Energy Storage Equality Constraints: Quantity of energy storage at the end of the day must be equal to the desired storage end value ($E_{S(end)}$).

$$E_{S(end)} = \sum_{t=1}^{24} (E_{C,t} - E_{D,t} + E_{S(start)}) \tag{16}$$

C. DAY-AHEAD LOAD AND PRICE FORECAST MODEL

As shown in fig. 2, a day-ahead price forecast model forecasts load sensitive price with the use of previously forecasted load. The load and price forecasting model is developed using two-layer Bayesian Regularization feed-forward Neural Network [28]. The inputs to this model include the next day's:

1) Weather parameters which consist of max/min dry bulb and max/min wet bulb temperatures.
2) Day type including identification of working day or not, and hour of the day.
3) Load trend information is given to forecaster with the help of previous day's same hour load, previous week's same hour load and previous weeks' average load.
4) Price trend information with the help of previous day's same hour price, previous week's same hour price and previous weeks' average price and forecasted load.

IV. SIMULATION AND RESULTS

A. LOAD AND PRICE FORECAST

The forecasting model is applied to predict electricity price and load using the real historical data (as shown in Appendix) from New York Independent System Operator (NYISO) [29]. Currently, NYISO provides price-based DR program including day-ahead dynamic pricing which is suitable for the proposed study. The forecasters are trained using the 18 months hourly data set from 1 April 2015 to 28 September 2016 for the New York City. The hourly data of 18 months resulted in 13128 samples of each input parameters, of which 70% of total samples were used as training of the forecaster. The rest of 30% samples were used for validation and testing of the forecaster. Fig. 3 and 4 shows the load and price forecasting results of forecasting model respectively.

One of the most widely-used criterions to measure forecasting error is the Mean Absolute Percentage Error (MAPE) [30]. MAPE measures error as a percentage of actual values and is formulated as,

$$MAPE = (100/n) \sum_{t=1}^{n} [|A_t - F_t|/A_t] \tag{17}$$

where A_t is the actual value, F_t is the forecasted value and n is the number of values forecasted. The MAPE of predicted load

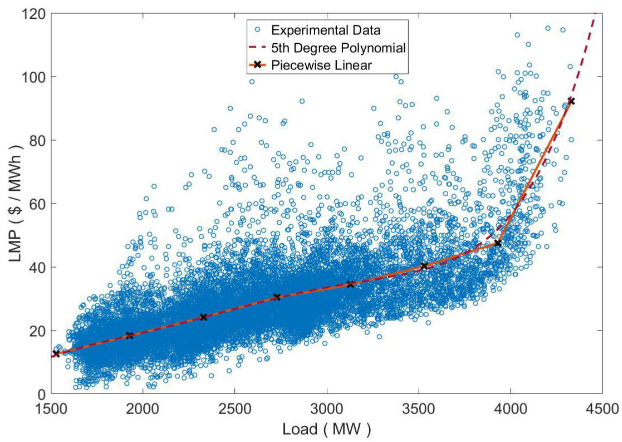

FIGURE 5. Relation between LMP and Load.

for the given 18 months of data (1 April 2015 to 28 September 2016) is 1.04 whereas for price it is found to be 7.78. The impact of high forecasting error on the energy storage optimization strategy can be significant. In order to include forecasting error in the energy storage optimization process, another factor of forecasting error need to be included in the optimization strategy which would increase complexity of the problem. Or as an alternative, forecasting technique can be improved to minimize the forecasting error as much as possible. In this study, the load and price forecasting is done preliminary for the energy storage optimization process. To reduce the complexity of the problem, we have not included forecasting error in the optimization process.

The relation between LMP and load is obtained and compared between piecewise linear regression and 5[th] degree polynomial regression as shown in fig. 5. Here it is observed that the relation between LMP and load is almost linear until the breakpoint which is found to be nearly at the load 4000MW. The average value of slope (M) before the breakpoint is 0.0145, whereas after the breakpoint it becomes 0.111. This sudden increase in M is due to the transmission network congestions which can be avoided with the implementation of large enough energy storage. Therefore, in this study we take the value of M as 0.0145.

B. ENERGY STORAGE OPTIMIZATION

The simulation is performed for two different energy storage sizes. Energy storage parameters considered in this study are described in Table 1.

For the proposed energy storage optimization, Matlab Quadratic Programming Solver was used. The results obtained in fig. 6 shows the optimized scheduling of charging and discharging of utility owned energy storage system while considering the overall impact of the large scale energy storage on the LMP.

These results can be compared with the optimization solutions as proposed in other studies. Fig. 7 shows the results of Linear Programming [31] based optimization for energy storage which does not consider impact of the large scale energy storage on the LMP. It took 9 iterations of linear programming solver to obtain first-order optimality condition in 0.363 seconds whereas for quadratic programming, 10 iterations were needed to reach first-order optimality condition in 0.174 seconds.

With fig. 7, it can be observed that the ESS scheduling optimization strategy without considering ΔLMP_t, energy storage charges/discharges at maximum charging/discharging rate even at slightest price arbitrage possibility. Whereas the proposed ESS scheduling optimization

TABLE 1. Energy storage properties.

Parameter	Description	Case 1	Case 2
$E_{S(max)}$	Maximum Storage Capacity	500 MWh	1 GWh
$E_{S(start)}$	Day Start Stored Energy	50 MWh	100 MWh
$E_{S(end)}$	Day End Stored Energy	50 MWh	100 MWh
$E_{C(max)}$	Maximum Charging Rate	125 MW	250 MW
α	Charging Efficiency	0.9	0.9
$E_{D(max)}$	Maximum Discharging Rate	125 MW	250 MW
β	Discharging Efficiency	0.9	0.9

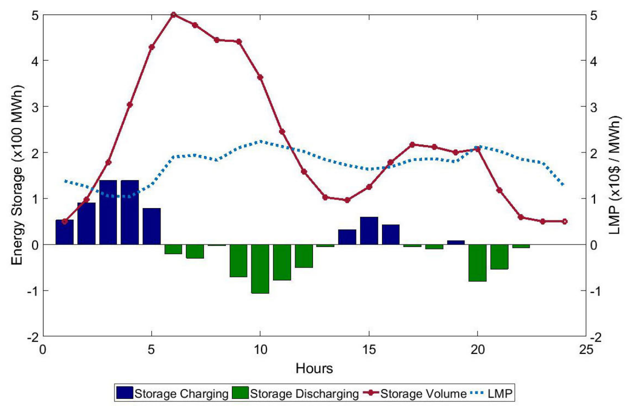

FIGURE 6. ESS scheduling considering ΔLMP_t (Case 1).

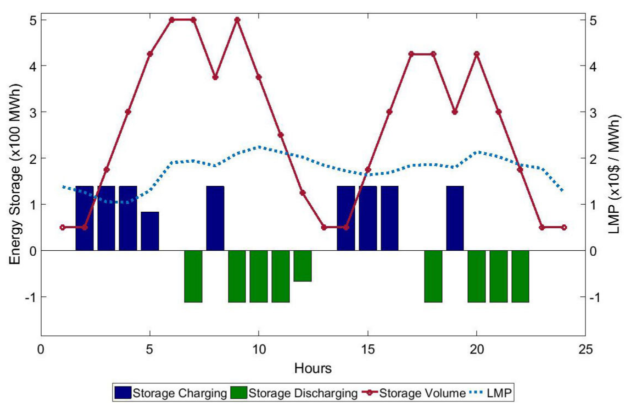

FIGURE 7. ESS scheduling without considering ΔLMP_t (Case 1).

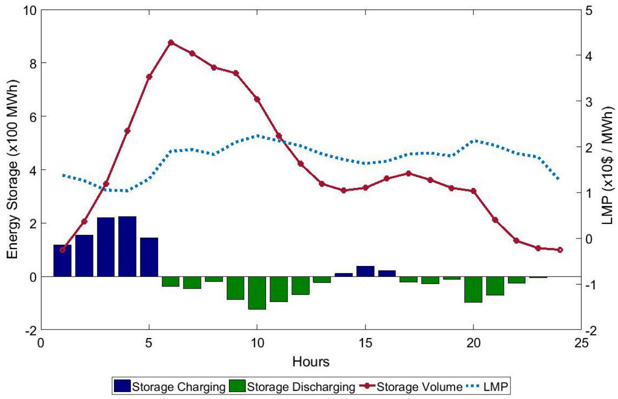

FIGURE 8. ESS scheduling considering ΔLMP_t (Case 2).

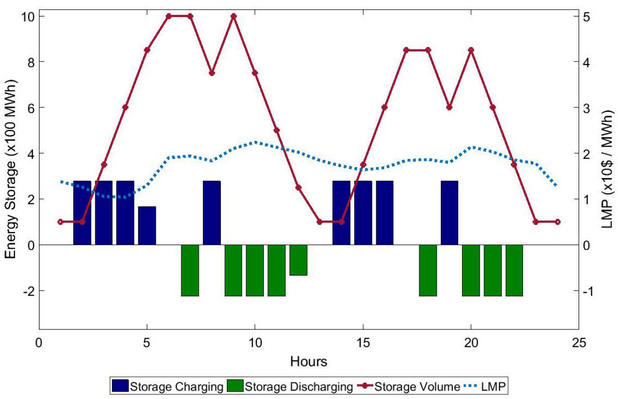

FIGURE 9. ESS scheduling without considering ΔLMP_t (Case 2).

considering ΔLMP_t as shown in fig. 6, considers the large scale charging/discharging of energy storage impact on the price curve and optimizes the amount of charging/discharging accordingly. Additional simulation with 1 GWh energy storage as shown in fig. 8 and 9 was also carried out to better understand the impact of larger scale energy storage charging and discharging on the price curve. In Case 2 of ESS scheduling optimization considering ΔLMP_t as shown in fig. 8, as the energy storage parameters were doubled, slight changes in the ESS scheduling can be observed as compared to Case 1. Whereas, the simulation for Case 2 in fig. 9 provided similar results for the ESS scheduling optimization without considering ΔLMP_t as it again performed charging/discharging of energy storage at maximum rate even at slightest price arbitrage possibility. Moreover, the ESS scheduling optimization strategy in fig. 8 did not utilize the storage capacity to the maximum limit (1 GWh). The optimal storage size with same storage charging/discharging parameters as in Case 2 is found to be 8800 MWh for the forecasted electricity price.

C. PRICE IMPACT

The impact of both strategies energy storage charging/discharging on LMP is analyzed with two different storage sizes (500MWh and 1GWh) and is shown in fig. 10 and 11.

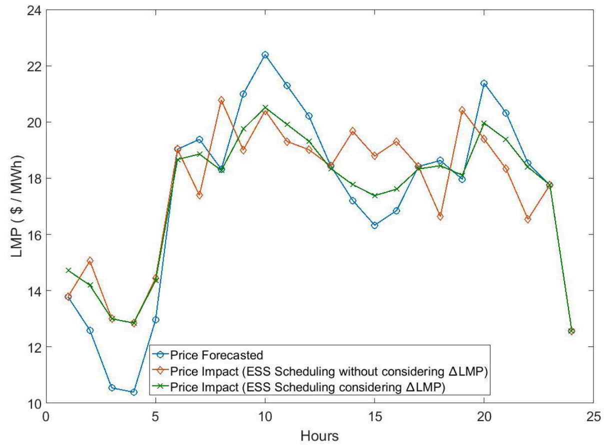

FIGURE 10. Price impact (Case 1).

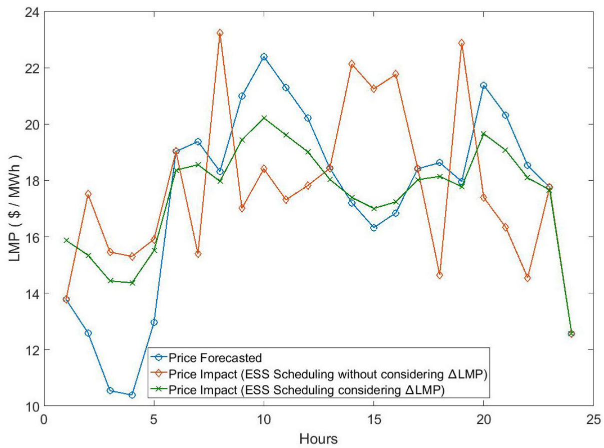

FIGURE 11. Price impact (Case 2).

TABLE 2. Retail profit.

Case	500 MWh	1 GWh
ESS scheduling without considering ΔLMP_t	\$ 2659.46	\$ 842.44
ESS scheduling considering ΔLMP_t	\$ 2816.26	\$ 2979.63

It can be observed in fig. 10 that the ESS scheduling without considering ΔLMP_t resulted in the price variation with spikes which became significantly larger as the storage size is increased as shown in fig. 11. Whereas the proposed ESS scheduling considering ΔLMP_t resulted in the improved smoothness of the price curve in both cases.

This variation in predicted price curve as shown above due to large scale energy storage charging and discharging will further affect the revenue generation from energy storage as planned by the utility. Table 2 compares the next day's revenue generated for the utility using both cases of ESS scheduling strategies with or without considering ΔLMP_t. When used larger storage size in this study, the ESS scheduling without considering ΔLMP_t caused

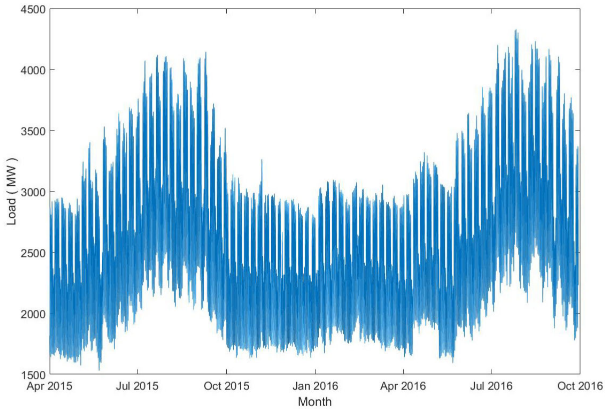

FIGURE 12. Historical load.

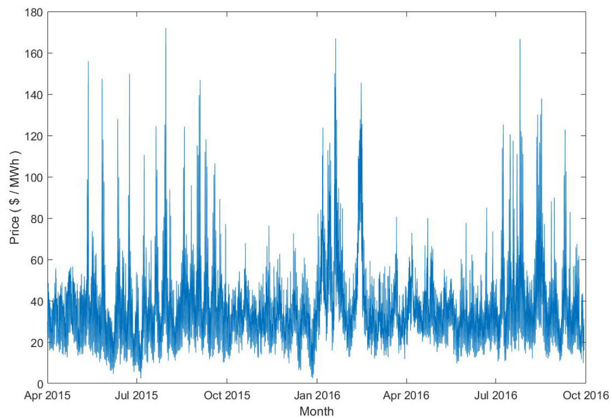

FIGURE 13. Historical price.

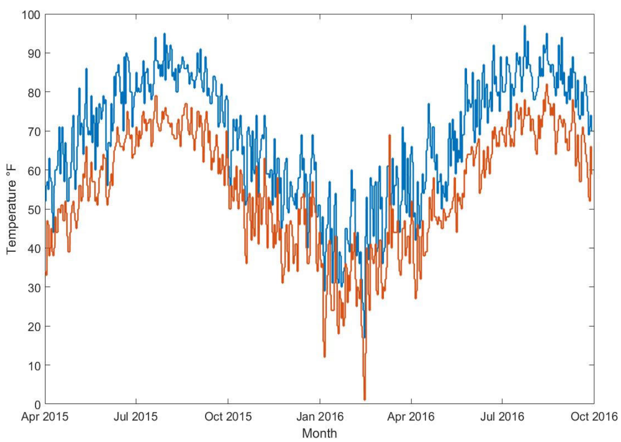

FIGURE 14. Historical dry bulb temperature.

high variation in price curve which resulted in much less revenue profit for the utility than before. Whereas, for the ESS scheduling considering ΔLMP_t, the larger storage size reduced the variation in the price curve which decreases the profit margin for buying and selling of the energy. Hence the revenue profit for the utility is similar as before.

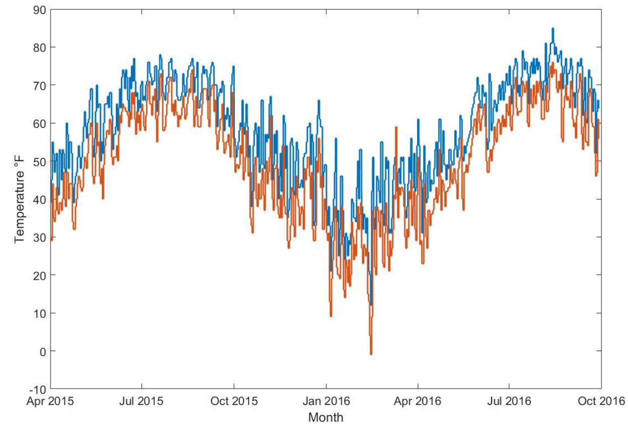

FIGURE 15. Historical wet bulb temperature.

V. CONCLUSION

Dynamic pricing schemes influence the end-users to adjust their load demand for the reliability of the system. Furthermore, dynamic pricing can also be seen as opportunities to maximize profit/minimize cost at the every level of the electric grid. Research has shown that utility owned energy storage system uniformly improves the retail profit and as the level of integration increases, the proportion of benefits goes to the consumers as well.

As the interest in large scale energy storages from the utility point of view is increasing, the pricing schemes will get smoother with the establishment of locational based marginal pricing which are more volatile to load changes in a particular location.

In this study, a forecasting model for day-ahead load and price is established for the planning and scheduling of utility owned energy storage system. The relation between load and LMP is discovered with the dynamic pricing and load data from NYISO. With the use of forecasted results and relation between LMP and load, an energy storage scheduling model was proposed to maximize utility's revenue while considering the volatility of LMP due to charging and discharging of the energy storage. The revenue maximization problem was solved using quadratic programming with linear constraints of the energy storage. As compared to conventional storage optimization approach, the results showed that our proposed model not only increased the revenue for the utility but also helped in smoothing the next day's electricity price curve.

APPENDIX

The dynamic pricing dataset for the New York City is obtained from NYISO [29]. Fig. 12-15 shows the historical hourly dataset of 18 months from 1 April 2015 to 28 September 2016 which includes LMP, load and temperature (dry bulb and wet bulb) respectively.

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