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Energy Management Strategy in a Residential Battery Energy Storage System*

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Abstract—**This paper examines the issue of energy management in a residential Battery Energy Storage System (BESS). The development of the energy management strategy (EMS) involves the modeling of the BESS and the modeling of a prediction aging mechanism for the Lithium Ion battery stack. In addition, EMS comprises the identification of the needs and requirements for energy management in a dynamic pricing environment where the Power Supplier (GRID) is the monadic source of power to the resident and to the BESS. The main objective of the proposed EMS is to prevent the fast aging of the Lithium-Ion batteries with respect to the maximum financial benefits for the consumer. Moreover, due to the dynamic pricing environment and the uncertainty that the forecast energy demand will match the actual energy demand, the ability of the EMS to update the proposed strategy during the day on hourly basis can be deemed vital. Indicative results of the proposed method are presented in order to demonstrate the ability of the BESS's to provide an optimal solution for covering the maximum energy demand with the minimum degradation effects for the batteries.**

I. INTRODUCTION

Over the past years the increasingly energy demand and the environmental pollution has led to the development of improved Renewable Energy Systems (RES) and energy storage systems. Applying BESS (With or without a renewable energy source) in households in order to reduce electricity bills is a significantly challenging issue since the high investment costs of the BESS make these systems unprofitable [1], [2]. Nevertheless, the economic viability is expected to be achieved as the prices of BESS continue to decrease. Furthermore, considering that the market price trend differs to each country these systems are going to be profitable in the very near future in many countries. In [3] it is proposed a methodology for calculating the Levelized Cost of Energy (LCOE) in a RES which consists of Photovoltaic (PV) and storage system. Moreover, in [1] an economic model which includes economical and battery aging parameters is analyzed and proves that a PV-storage system will be profitable in the near future in the German market. In addition, in [2] another economic model which considers battery aging behavior is presented and proves that a PV-storage system is already viable in some scenarios on the German market.

The issue of accurate prediction of a Lithium Ion battery life is of major importance as it can prove if the investment costs for the BESS are going to be covered. Lithium Ion batteries degradation is affected by the environment temperature, charging rate, discharging rate, depth of discharge, number of cycles and time intervals between full charge cycles [4], [5], [6]. Various models have been developed in order to predict the capacity. In [7] it is proposed a semi-empirical model which predicts the battery degradation based on: a) time, b) temperature, c) charging/discharging rates (C-Rate) and d) depth of discharge (DOD). Last but not least, in [8] it is analyzed a multi-stress factor model which contains the aforementioned stress factors including the taper voltage of the battery.

The goal of this paper is to propose an optimal energy strategy of a BESS without renewable energy source which will operate on a dynamic pricing environment. The EMS will update the proposed discharging profile of the BESS according to the updated price profile and the updated forecasted energy demand profile in order to maximize the profit and minimize the aging of the BESS.

II. BATTERY ENERGY STORAGE SYSTEM

The system to be considered comprises 15 Lithium Ion battery cells (Model: GBS-LFP100Ah-A) of 100Ah capacity connected in series. It is developed at the laboratory of Process Systems Design & Implementation (PSDI) of Chemical Process and Energy Resources Institute/Centre for Research and Technology Hellas (CPERI/CERTH). The nominal voltage of each cell is 3.2V, hence the BESS operates at 48V and the maximum power capacity is 4.8kW.

The BESS will be applied in households for parallel operation with the GRID (Fig.1).

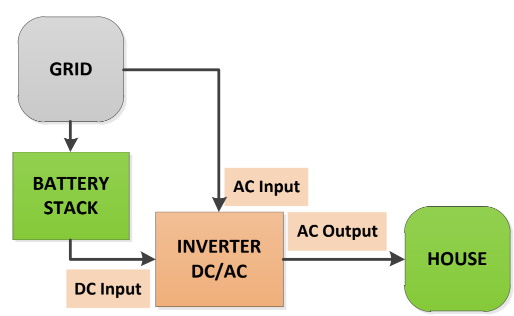

Figure 1. BESS Connection (Parallel Operation)

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Non parallel operation would be inefficient since it can result to dead time during transition and interrupting power supply to the household. This is because at this scenario GRID and BESS are not able to supply power to the household simultaneously. GRID is not connected to the inverter and there is a switch between GRID and the output of the inverter.

Therefore, the household receives power from the one source or the other. The notable advantage of the parallel operation is the elimination of the dead time and the interrupting power supply.

III. BATTERY AGING PREDICTION

Due to lack of aging related experimental data for the Li-ion 100 Ah batteries, the capacity loss estimation was implemented by using the proposed approach from the validated multi-stress factor model of [8].

A. Battery Aging Model

The capacity loss of the battery can be calculated by (1).

$$Q_{loss} = A * exp\left(\frac{-E_a}{RT}\right) n^z \quad (1)$$

TABLE I. BATTERY AGING PARAMETERS

Variable	Description	Unit
Q_{loss}	Capacity loss	Ah
A	Pre-exponential factor	Ah
E_a	Activation Energy	J/mol
R	Gas constant	$J*mol^{-1}*K^{-1}$
T	Temperature	K
n	Number of cycles	
z	Cycles exponent	

The parameters which must be identified in order to validate the model are the pre-exponential factor A, the activation energy E_a and the cycle's exponent z. In [8] the exponent z is set to be constantly 0.74, the pre-exponential factor is calculated by (2) and the activation energy by (3). Equations (2), (3) are obtained as an outcome of the data fitting process [8].

$$A(DOD, C, V_t) = -157.671 + 3.624DOD + 14.19C + 2.721(e^{0.938V_t}) \quad (2)$$

$$E_a = 2330 * e^{1.337C} + 13530 \quad (3)$$

where DOD is the depth of discharge, C is the charging/discharging rate and V_t is the taper voltage.

B. Aging Prediction Results

Assuming that the BESS is located inside the household the environment temperature is from 20°C to 25°C. Therefore, the temperature is not going to affect the lifetime expectancy of the 15-battery stack. In Fig.2 the predicted capacity loss for DOD=30% and various C-rates is presented. It is plainly shown that high C-rates can cause a significant damage.

Simulating the model for depth of discharge 70% proves that by increasing the DOD the capacity loss is increasing significantly (Fig.3). Hence, a combination of deep discharges and high C-rates will result to the increment of the capacity fade excessively.

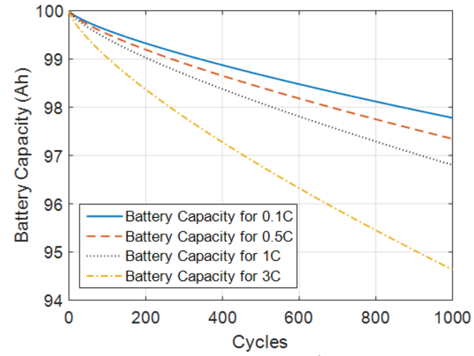

Figure 2. Battery aging for T=20°C and DOD=30%.

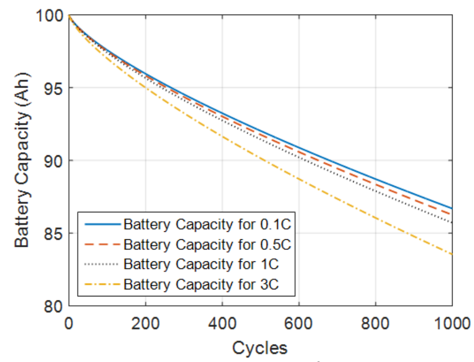

Figure 3. Battery aging for T=20°C and DOD=70%.

IV. ENERGY MANAGEMENT STRATEGY

The average household electricity consumption varies according to house's dimensions and geographical location. Ordinarily, the electricity consumption is between the range 5kW-50kW. Considering that the BESS can store and provide maximum 4.8kW, it is evident the need of an energy management strategy in order to achieve the maximum economic profit with the minimum possible degradation of the BESS.

A. Optimization Formulation

The EMS segregates the day to two zones: a) charging zone and b) discharging zone. The BESS's charging occurs during night from midnight to 8 a.m. and the discharging from 8 a.m. to midnight. The discharging zone is divided to sixteen hourly timeslots. Initially, the EMS defines the amount of energy which is going to be supplied in each one of the sixteen time slots according to the day-ahead power demand profile and the day-ahead price profile (Fig.A1, Fig.A2 in Appendix A).

The goal is to supply energy to the house during the high price time slots (Fig.A2) by reaching the maximum permissible depth of discharge which is defined by the battery's manufacturer. The optimization problem is stated as:

$$\min_x f(x) = \sum_{i=1}^{16} (y_i - x_i) \quad (4)$$

$$\text{s.t. } x_i \leq y_i, i = 1, \dots, 16$$

$$x_i \leq 2400, i = 1, \dots, 16$$

$$\sum_{i=1}^{16} x_i \leq P_{bat}$$

where y_i is the energy demand at each time slot, x_i is the supply energy at each time slot and P_{bat} is the available power at the battery stack.

The standard discharge current proposed by the manufacturer is 50A. In order to guarantee that the discharge rate will not exceed 0.5C, the maximum energy supply in each hourly time slot is set at 2400Wh.

Considering the dynamic pricing environment the EMS updates the optimal discharge solution after the end of each time slot. Furthermore, it takes under consideration any possible updates on the power demand forecast profile and the actual supplied energy at the previous time slots in order to calculate the remaining available power at the battery stack. Therefore, the objective function (Eq. 4) is rearranged hourly during the day. The optimization problem is stated as:

$$\min_x f(x) = \sum_{i=ts}^{16} (y_i - x_i) \tag{5}$$

$$\text{s.t. } x_i \leq y_i, i = ts, \dots, 16$$

$$x_i \leq 2400, i = ts, \dots, 16$$

$$\sum_{i=ts}^{16} x_i \leq P_{bat,} P_{bat} = 3360W$$

$$P_{bat(j)} = 3360W - P_{bat(j-1)}\ j = 2, \dots, 16 \tag{6}$$

where ts is the number of current time slot.

B. Optimization based on financial criteria

The financial based optimization targets to achieve the maximum allowed depth of discharge of the batteries at the most expensive time slots of the day. Hence:

$$x_i = 0\ if\ p_w < 3, w = 9, \dots, 25\ and\ i = 1, \dots, 16 \tag{7}$$

where p_w is the price weight.

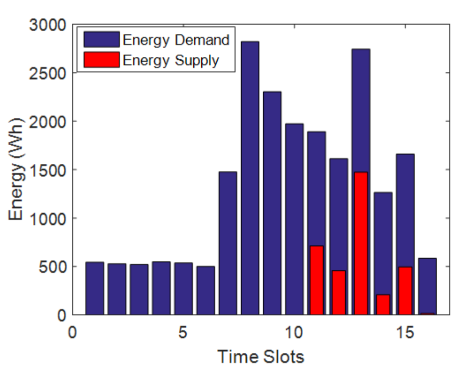

Figure 4. Financial based optimization at 8am

By setting the maximum permissible depth of discharge at 70% (3360W) the optimization algorithm was run before the first time slot (8 a.m.). The simulation of the dynamic optimization algorithm for the EMS was implemented in Matlab. It considers the day-ahead profiles (Fig.A1, Fig.A2 in Appendix A), the objective function subject to the given constraints ((5), (6), (7)) and defines the optimal solution to maximize the profit (Fig.4).

Assuming that until 14 p.m. the price profile was not altered the optimization algorithm proposes the exact similar discharge profile at the first six updates. At 14 p.m. the price profile and the power demand profile were altered (Fig.A3, Fig.A4 in Appendix A). In Fig.5 the updated optimal solution is presented.

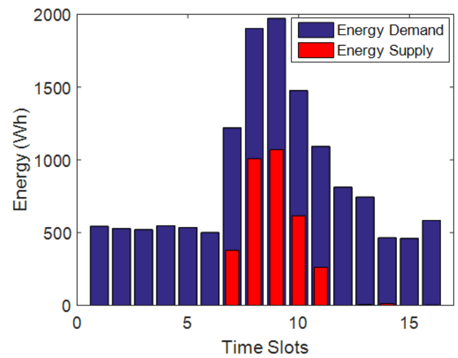

Figure 5. Financial based optimization at 14pm

At 16 p.m. the power demand profile was altered again (Fig.A5 in Appendix A). It is observed that from 14 p.m. to 16 p.m. the actual energy demand matches the forecast profile. The remaining available stored power is 1997.6W and it is going to be supplied according to Fig.6. Assuming that until midnight the price and power profiles were not modified, Fig.6 represents the overall power consumption of the BESS at the end of the day. It is observed that due to the low energy demand after 16 p.m. the EMS did not manage to reach the maximum depth of discharge. The BESS supplied 2942.4W at the house which corresponds to 61.3% depth of discharge. Although, the BESS could supply power from 20 p.m. to 21 p.m. and from 22 p.m. to 23 p.m. (time slots 12, 15) the low price weights did not satisfy the financial constraint.

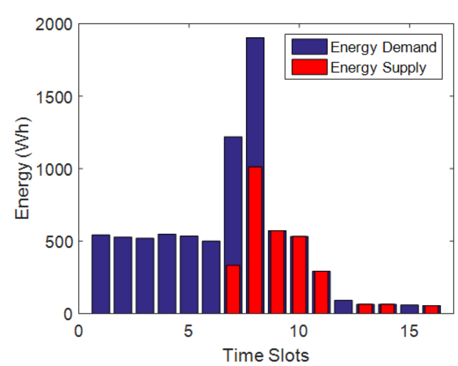

Figure 6. Financial based optimization at 16pm

In scenarios where the actual power demand is significantly lower than the forecasted demand like the one described above, the optimization algorithm could contain an option to abolish the financial constraint and drive the BESS to supply to the house as much power as possible. However, this would have been inefficient as the deep depth of discharge would result to higher aging for the batteries and at the same time the financial profit would be minimum.

C. Optimization based on aging criteria

The aging based optimization, targets to achieve the minimum degradation effects for the BESS. This could be achieved by two methods. The first method is to fully discharge the batteries (DOD=70%) at time slots with low discharging rates. Commonly, low discharge rate at a time slot implies low price weight. Therefore, from financial perspective this method might be inefficient in some cases. The second methodology is to apply low depth of discharge at the expensive time slots. The aging weights defined as:

$$\begin{gathered} I \leq 10A \Rightarrow a_w = 5 \\ 10A < I \leq 15A \Rightarrow a_w = 4 \\ 15A < I \leq 30A \Rightarrow a_w = 3 \\ 30A < I \leq 40A \Rightarrow a_w = 2 \\ 40A < I \leq 50A \Rightarrow a_w = 1 \end{gathered} \tag{8}$$

where a_w is the aging weight.

Considering the first methodology, the maximum discharge current is set at 15A. Hence:

$$x_i = 0 \; if \; a_w \leq 3, w = 1, \dots, 16 \; and \; i = 1, \dots, 16 \tag{9}$$

Simulating the first methodology with respect to the power demand profile in Fig.A1, Fig.7 was obtained. The maximum depth of discharge was achieved by supplying power from 8 a.m. to14 p.m. and 23 p.m. to 24 p.m. In Fig.7 it is shown that the BESS supplies around 500W at each time slot which denotes that the average current is 10.4A considering the nominal voltage is 48V.

At the second methodology the maximum depth of discharge is set at 40%. Therefore, the maximum possible power supply is 1920W. Furthermore, the price weight constraint is altered in order to supply energy only at the two most expensives hourly time slots of the day (Fig.A2).

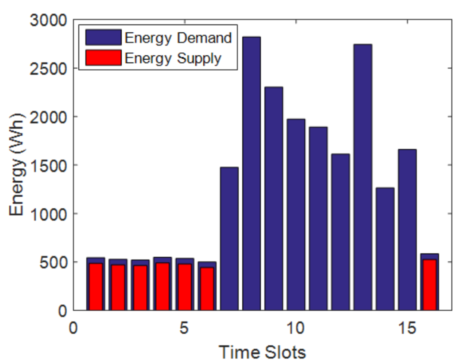

Figure 7. Aging based optimization method 1

$$x_i = 0 \; if \; p_w \leq 4, w = 9, \dots, 25 \; and \; i = 1, \dots, 16 \tag{10}$$

The discharge profile at Fig.8 was obtained by simulating this methodology with respect to profiles Fig.A1 and Fig.A2. It was noted that the BESS supplies 1064W (I=22.1A) between 20 p.m.-21 p.m. and 856W (I=17.8) between 21 p.m.-22 p.m. Thus the average discharge current is 20A.

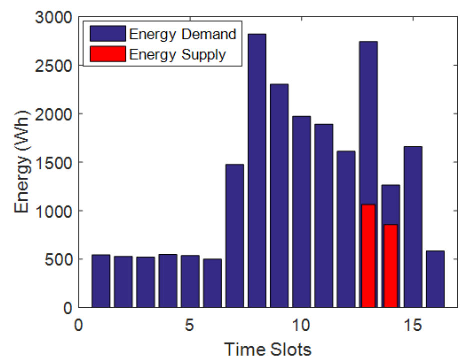

Figure 8. Aging based optimization method 2

D. Comparison between financial and aging optimization

The comparison of the performance of the three proposed methodologies regarding the degradation effects at the batteries is crucial since the main objective of the EMS is to maintain the system's life expectancy.

The capacity loss is calculated for each one of the above-mentioned methods by using the aging prediction equations (1), (2), (3). Assuming constant environmental temperature (20°C) and invariability of the price and power demand profiles for 1000 cycles the BESS degradation is calculated. In Fig.9 it is observed that the best performance is achieved by the second aging optimization method which is implemented by applying low depth of discharge. More specifically the optimization based on financial criteria (Method 1) will result to the reduction of the capacity by 13.32Ah, the aging based optimization with low C-rates (Method 2) will result to 13.31Ah capacity loss and finally the optimization based on low DOD (Method 3) will decrease the capacity from 100Ah to 94.9Ah. The failure of method 2 to provide a better outcome than the method 1 is explained by the fact that the DODs at the two methods of the simulated scenario were equal (70%) and the average discharge currents were almost equal (11.6A in method 1, 10.4A in method 2). Contrariwise, in method 3 the DOD was 40% and the average discharge current 20A. The uncertainty that the actual power demand will match the forecasted profile is a high disadvantage in method 2, as it can result to significant alternations in the predicted discharge currents. Hence, the low DOD method can be deemed more efficient in preventing the battery aging.

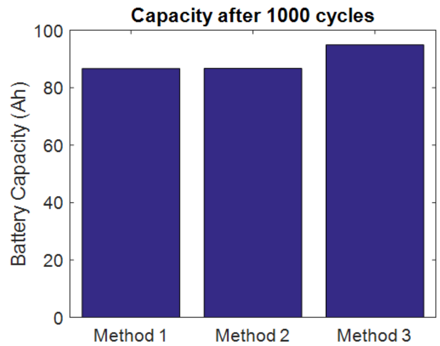

Figure 9. Comparison of the 3 optimization methods

E. Combined optimization

In order to prevent the fast aging of the batteries without applying low depths of discharge every day, a combined optimization was implemented (Fig.10). This algorithm comprises the following three subsystems: a) financial based optimization, b) aging based optimization and c) aging detection mechanism.

The aging detection mechanism arbitrates the operation of the other two subsystems in order to avoid the simultaneously operation. Firstly, an aging target is set. Afterwards, the financial optimization is enabled. Every 100 cycles the detection mechanism will calculate the deviation between the aging target and the actual aging. Thereafter, it will disable the financial based optimization and will enable the aging based optimization in order to compensate the deviation of the aging (if it is necessary). The aging compensation problem is stated based on (1), (2) and (3).

$$T_a = A_a(11) \Rightarrow$$

$$T_a = A_{A_a} * exp\left(\frac{-E_{A_a}}{RT}\right) n^z \Rightarrow$$

$$\frac{T_a}{exp\left(\frac{-E_{A_a}}{RT}\right) n^z} = -157.671 + 3.624DOD + 14.19C + 2.721(e^{0.938V_t}) \Rightarrow$$

$$DOD = \frac{\frac{T_a}{exp\left(\frac{-E_{A_a}}{RT}\right) n^z} + 157.671 - 14.19C - 2.721(e^{0.938V_t})}{3.624} \quad (12)$$

where T_a is the target aging and A_a the actual aging. Eq.12 calculates the DOD which should have been applied during the previous 100 cycles in order to achieve the aging target. The DOD for the aging based optimization is calculated by Eq.13.

$$DODag = DODf - 2 * (DODf - DOD) \quad (13)$$

where $DODf$ is the depth of discharge in the financial based optimization and $DODag$ is the depth of discharge which is going to be applied for the next 100 cycles in order to compensate the increased occurred capacity loss.

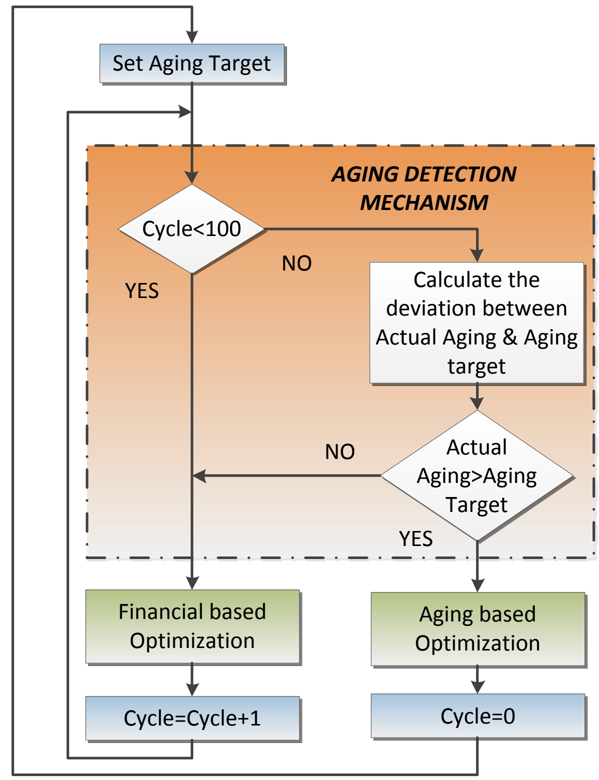

Figure 10. Combined Optimization

For instance, by setting the desirable aging to match the prediction of DOD=70% and C-rate=0.1 the aging target is 2.41Ah (after 100 cycles). Assuming that the actual average C-rate was 0.2 instead of 0.1, the DOD which should have been applied in order to achieve the target is calculated by Eq.12 and it is 69.59%. Therefore, by Eq.13 it is obtained the $DODag$ which is going to be applied for the following 100 cycles and it is 69.18%.

V. Conclusion

The aforementioned work has approached the energy management of a residential battery energy storage system from the sight of the battery pre-mature aging prevention. An optimization algorithm was implemented, in order to supply the maximum possible power to the house by taking under consideration the dynamic pricing environment and the alterability of the power demand profile during the day. Moreover, a validated aging prediction model was used in order to prevent the pre-mature aging of the batteries. The proposed method has the potential for future incorporation with a detailed Battery Energy Storage System cost analysis in order to demonstrate if it is feasible to achieve financial viability and maintainability of the storage system's life expectancy.

APPENDIX A

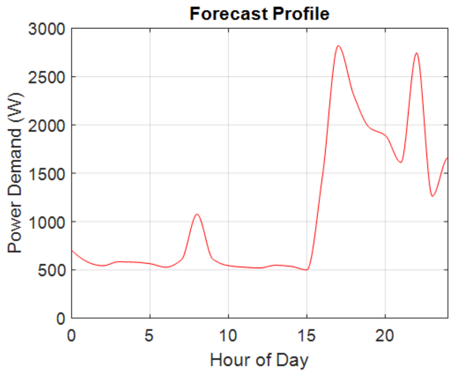

Figure A.1 Power Demand forecast profile 8 a.m.

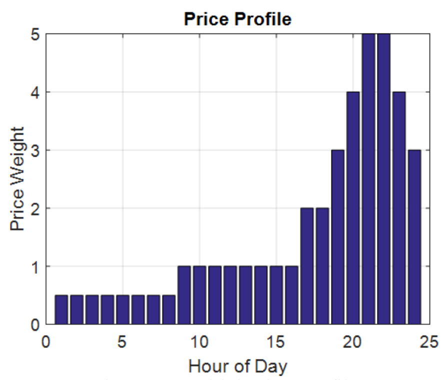

Figure A.2 Initial Price profile.

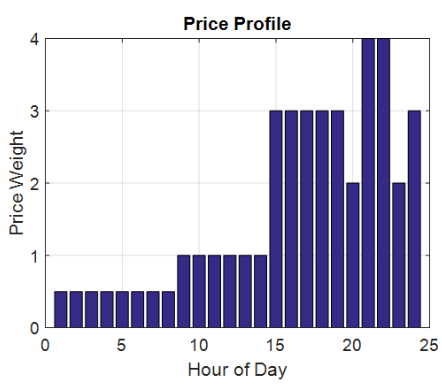

Figure A.3 Price profile update at14 a.m.

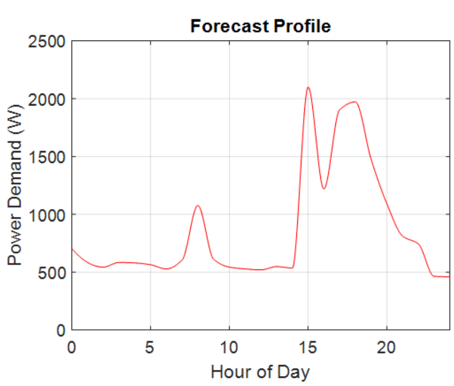

Figure A.4 Power Demand profile update at 14 a.m.

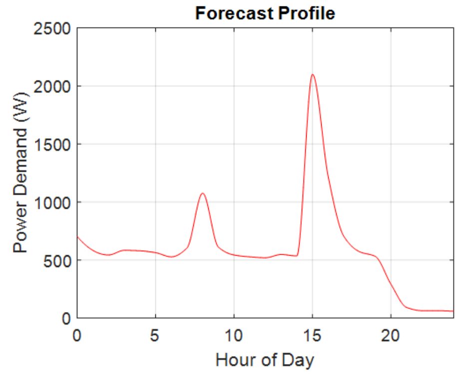

Figure A.5 Power Demand profile update at 16 p.m.

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