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Optimal Time-of-Use Management with Power Factor Correction Using Behind-the-Meter Energy Storage Systems

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***Abstract*—In this work, we provide an economic analysis of using behind-the-meter (BTM) energy storage systems (ESS) for time-of-use (TOU) bill management together with power factor correction. A nonlinear optimization problem is formulated to find the optimal ESS's charge/discharge operating scheme that minimizes the energy and demand charges while correcting the power factor of the utility customers. The energy storage's state of charge (SOC) and inverter's power factor (PF) are considered in the constraints of the optimization. The problem is then transformed to a Linear Programming (LP) problem and formulated using Pyomo optimization modeling language. Case studies are conducted for a waste water treatment plant (WWTP) in New Mexico.**

***Index Terms*—Energy storage, behind-the-meter (BTM), time-of-use (TOU), net metering (NEM), peak shaving, load leveling, demand charge, distribution system, optimization, Mixed Integer Nonlinear Programming (MINLP), Linear Programming (LP).**

I. Introduction

Over the last decade, mandates and incentives for energy storage have increased dramatically. For example, in 2013 the CPUC passed a mandate for 1.3 GW of grid storage to be installed by 2020 in California [1]. Similarly, a number of states including New York and Massachusetts have announced initiatives and adopted policies adding a significant amount of energy storage to their infrastructure. This favorable policies give energy storage the opportunity to provide multiple services to the grid and to the customers. On the grid's side, energy storage could provide ancillary services to the wholesale markets such as frequency regulation, forward capacity, or spinning/non-spinning reserve [2]. On the customers' side, energy storage can also provide a wide range of applications such as on-site back-up power, PV utilization, demand charge reduction or time-of-use management [3].

Although energy storage can technically provide grid-side and customer-side services, the overall economic gains of energy storage deployments are limited by the round-trip efficiency and the capital costs of the ES devices [4]. Therefore, it is critical to assess the technical and economic benefits of energy storage systems in different applications to justify their deployment. In the literature, a number of works have evaluated the economic benefits of ESSs for generation, transmission and distribution applications. In [5], the profit of battery energy storage systems (BESS) for primary frequency control is maximized under a planning and control framework. The maximum potential revenues of ESSs for energy arbitrage and frequency regulation in different market areas are estimated in [6–9]. The revenue of energy storage from energy arbitrage and its contribution to transmission congestion relief is studied in [10]. The financial benefits of BESSs for T&D upgrade deferral is evaluated in [11]. The optimal operation of BESSs for mitigating PV variability and reducing transformers' losses is studied in [12]. A comprehensive review of ES benefits for grid-side applications is presented in [13].

On the other hand, only a few studies have evaluated the technical and economic benefits of energy storage for behind-the-meter (BTM) applications. Most of the studies focused on peak shaving using energy storage [14–16]. In [17], the optimal operation of energy storage for demand charge reduction is studied; however, the trade-off between demand charge saving and energy loss in ESS is not captured. In [18], energy charge and demand charge reduction for commercial buildings are co-optimized but the negative net consumption caused by on-site PV generation is not considered. Our previous work in [3] proposes an approach that co-optimizes energy charge, demand charge and net-metering credit, thereby minimizing the monthly electricity bill for time-of-use (TOU) and net-metering (NEM) customers.

Nevertheless, none of the above works have discovered the benefits of behind-the-meter ESSs for reactive power applications. This type of applications is enabled by the recent improvement in power electronics technologies that allow the power inverters to inject/absorb reactive power while transferring real power to charge or discharge the storage device. To maximize the overall economic benefit of its deployment for these applications, an ESS must be optimally managed so that it can efficiently deliver real and reactive power simultaneously for different purposes.

In this paper, we propose an approach to maximize the economic benefit of BTM energy storage for time-of-use (TOU) management while providing power factor correction. This approach is best suited for large commercial or industrial customers who are often billed for their high peak demand and penalized for their low power factors. Although these types of customers might already correct their power factors to meet the utilities' requirements, these power corrections will not be sufficient if large amount of PV is installed. Therefore, the benefit of BTM energy storage can be magnified in this case.

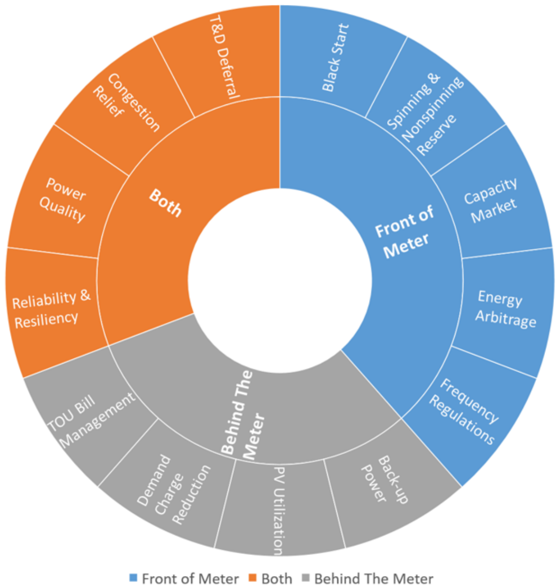

Fig. 1. Energy storage applications

In the proposed approach, a Mixed Integer Nonlinear Programming (MINLP) problem is formulated to find the optimal ESS's charge/discharge operating scheme that minimizes the monthly electricity bills while correcting the power factor of the customers. The linear constraints of this problem are based on the energy-flow state of charge (SOC) model [6] and the inverter's power factor limits. The problem is then transformed to a Linear Programming (LP) problem using Minimax technique. The approach assumes perfect foresight of data and therefore provides the results for the best-case scenario.

The rest of the paper is organized as follows: section II.A presents the energy-flow SOC model; section II.B provides details about inverter's reactive power capability; section II.C presents the formulation of the optimization problem; case studies are conducted in section III; concluding remarks are found in section IV.

II. Optimization Problem Formulation

A. Energy-flow state of charge model

The storage parameters are shown in Table I. In this paper, we define decision variables P_i^{d} as the discharge power and P_i^{c} as the charge power seen at the AC side of the inverter. Therefore, the state of charge (SOC) S_i at any time i can be expressed as:

$$S_i = \gamma_{\mathrm{s}} S_{i-1} + \gamma_{\mathrm{c}}(P_i^{\mathrm{c}} - P_i^{\mathrm{lc}})\tau - (P_i^{\mathrm{d}} + P_i^{\mathrm{ld}})\tau/\gamma_{\mathrm{d}}, \ \forall i \in \mathrm{H} \quad (1)$$

which states that the SOC at time i is the sum of the SOC at time $i-1$ and the net charging energy (adjusted by the storage charge/discharge efficiencies and inverter losses P_i^{lc} during charge and P_i^{ld} during discharge).

TABLE I
ESS Parameters

Symbol	Description
τ	Time period length (e.g., one hour)
H	Set of time periods in the optimization
$\overline{P}$	Power rating of the inverter [kVA]
$\overline{S}$	Maximum energy storage capacity [kWh]
S	State of charge [kWh]
γ_{s}	Storage efficiency over one period [%]
γ_{c}	Energy storage charge efficiency [%]
γ_{d}	Energy storage discharge efficiency [%]
$\overline{\Phi}$	Power factor angle limit of the inverter [rad]

The SOC must be within its physical limits as described in the following constraint:

$$0 \leq S_i \leq \overline{S}, \forall i \in \mathrm{H} \quad (2)$$

It should be noted that the "available" capacity at time i is $\gamma_{\mathrm{d}} S_i$ because of the discharge efficiency. Therefore, $\overline{S} = X/\gamma_{\mathrm{d}}$ where $X(kWh)$ is the rating capacity given in the system specification data.

Zero net charging constraint (i.e., the SOC at the last period is equal to the initial SOC) is also used in this paper:

$$\tau \sum_{i \in \mathrm{H}} \gamma_{\mathrm{c}}(P_i^{\mathrm{c}} - P_i^{\mathrm{lc}}) - (P_i^{\mathrm{d}} + P_i^{\mathrm{ld}})/\gamma_{\mathrm{d}} = 0 \quad (3)$$

B. Reactive capability of power inverter

For power factor correction application, the ESS's inverter is always required to inject reactive power while injecting or absorbing real power. In other words, the inverter is always operating in the 1st-quadrant and the 4th-quadrant. In order to raise the power factor over a predefined set point $pf^* = \cos(\phi^*)$ (lagging), the reactive power output of the inverter must satisfy the following constraint:

$$0 \leq Q_i^{\mathrm{load}} - (Q_i^{\mathrm{c}} + Q_i^{\mathrm{d}}) \leq \tan(\phi^*) P_i^{\mathrm{net}} \quad (4)$$

where Q_i^{c} and Q_i^{d} are the decision variables that represent the reactive power output of the inverter during charge and discharge at time i; P_i^{net} is the real net load and Q_i^{load} is the reactive load at time i. It should be noted that Q_i^{c} and Q_i^{d} are non-negative variables and mathematically do not occur at the same time period. Therefore, $(Q_i^{\mathrm{c}} + Q_i^{\mathrm{d}})$ represents the actual reactive power output of the inverter at time i.

As characterized in [19], the efficiency of an inverter working in these modes decreases as higher voltage and current ripples occur. The power loss in the inverter is very dependent on its real and reactive power outputs. In this paper, the inverter losses during charge and discharge at time i are approximated as linear functions of charge and discharge powers:

$$P_i^{\mathrm{lc}} = k_{\mathrm{c}}^{\mathrm{p}} P_i^{\mathrm{c}} + k_{\mathrm{c}}^{\mathrm{q}} Q_i^{\mathrm{c}} \quad (5)$$
$$P_i^{\mathrm{ld}} = k_{\mathrm{d}}^{\mathrm{p}} P_i^{\mathrm{d}} + k_{\mathrm{d}}^{\mathrm{q}} Q_i^{\mathrm{d}} \quad (6)$$

TABLE II
NOMENCLATURES

Symbol	Description
m	Month m
$\mathrm{pr_i}$	TOU energy price at time i [$/kWh]
$\mathrm{pr_i^s}$	Market energy price at time i [$/kWh]
α_i	Binary variable at time i
$\mathrm{k_{pf}}$	Penalty factor due to low power factor
P_i^{c}, P_i^{d}	Decision variables: charge and discharge power at time i [kW]
Q_i^{c}, Q_i^{d}	Decision variables: reactive power output during charge and discharge at time i [kW]
P_i^{load}, P_i^{re}	Load and renewable power at time i [kW]
$\mathrm{C_E^m}$, $\mathrm{C_N^m}$, $\mathrm{C_D^m}$	Energy, net-metering and demand charges [$]
$\mathrm{d_{max}^m}$, $\mathrm{d_{pk}^m}$, $\mathrm{d_{ppk}^m}$	Rates for maximum demand and highest demands during peak and part-peak hours [$/kW]
$\mathrm{H^m}$, $\mathrm{H_{pk}^m}$, $\mathrm{H_{ppk}^m}$	Sets of hours, peak hours and part-peak hours

where $k_{\mathrm{c}}^{\mathrm{p}}$, $k_{\mathrm{c}}^{\mathrm{q}}$, $k_{\mathrm{d}}^{\mathrm{p}}$, and $k_{\mathrm{d}}^{\mathrm{q}}$ are the coefficients of the best fits.

Due to the physical limits of the inverter, the following constraints must be met at all times:

$$0 \leq Q_i^{\mathrm{c}} \leq \tan \overline{\Phi} P_i^{\mathrm{c}} \tag{7}$$
$$0 \leq Q_i^{\mathrm{d}} \leq \tan \overline{\Phi} P_i^{\mathrm{d}} \tag{8}$$
$$(P_i^{\mathrm{c}})^2 + (Q_i^{\mathrm{c}})^2 \leq (\overline{P})^2 \tag{9}$$
$$(P_i^{\mathrm{d}})^2 + (Q_i^{\mathrm{d}})^2 \leq (\overline{P})^2 \tag{10}$$

in which constraints (7) and (8) guarantee the inverter power factors are greater than its power factor limits, and constraints (9) and (10) ensure that the inverter's apparent power is less than its power rating. It can be seen that (9) and (10) are non-linear but convex. However, to simplify the problem these constraints are linearized as follows:

$$a_1 Q_i^{\mathrm{c}} + b_1 P_i^{\mathrm{c}} \leq c_1 \overline{P} \tag{11}$$
$$a_2 Q_i^{\mathrm{c}} + b_2 P_i^{\mathrm{c}} \leq c_2 \overline{P} \tag{12}$$
$$a_1 Q_i^{\mathrm{d}} + b_1 P_i^{\mathrm{d}} \leq c_1 \overline{P} \tag{13}$$
$$a_2 Q_i^{\mathrm{d}} + b_2 P_i^{\mathrm{d}} \leq c_2 \overline{P} \tag{14}$$

in which the coefficients $a_{(.)}$,$b_{(.)}$, and $c_{(.)}$ are given as:

$$\begin{array}{ll} a_1 = 1 - \cos(\overline{\Phi}/2) & a_2 = \cos(\overline{\Phi}/2) - \cos(\overline{\Phi}) \\ b_1 = \sin(\overline{\Phi}/2) & b_2 = \sin(\overline{\Phi}) - \sin(\overline{\Phi}/2) \\ c_1 = \sin(\overline{\Phi}/2) & c_2 = \sin(3\overline{\Phi}/2) \end{array} \tag{15}$$

C. Problem formulations

The cost minimization problem can be formulated as follows where variables and all parameters are defined in Table II.

$$\min\{\mathrm{k_{pf}}(\mathrm{C_E^m} + \mathrm{C_D^m}) + \mathrm{C_N^m}\} \tag{16}$$

s.t. (2) to (8) and (11) to (14), where

$$\mathrm{C_E^m} = \tau \sum_{i \in \mathrm{H^m}} \alpha_i P_i^{\mathrm{net}} \mathrm{pr}_i \tag{17}$$
$$\mathrm{C_N^m} = \tau \sum_{i \in \mathrm{H^m}} (1 - \alpha_i) P_i^{\mathrm{net}} \mathrm{pr}_i^{\mathrm{s}} \tag{18}$$
$$\mathrm{C_D^m} = \max_{i \in \mathrm{H^m}} \{P_i^{\mathrm{net}}\} \mathrm{d_{max}^m} + \max_{j \in \mathrm{H_{pk}^m}} \{P_j^{\mathrm{net}}\} \mathrm{d_{pk}^m} + \max_{k \in \mathrm{H_{ppk}^m}} \{P_k^{\mathrm{net}}\} \mathrm{D_{ppk}^m} \tag{19}$$

with $P_i^{\mathrm{net}} = P_i^{\mathrm{load}} - P_i^{\mathrm{re}} + P_i^{\mathrm{c}} - P_i^{\mathrm{d}}$ and α_i ($\forall i \in \mathrm{H^m}$) is binary and defined as follows:

$$\alpha_i = \begin{cases} 1 & \text{if } P_i^{\mathrm{net}} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

By enforcing constraint (4), the power factor can be sufficiently corrected. Therefore, $\mathrm{k_{pf}}$ is assumed to be 1.

The above problem is categorized as a Mixed Integer Nonlinear Programming (MINLP) problem which is computationally expensive to solve directly. We tackle this problem by removing binary variables in (17) and (18) using the following technique:

$$\alpha_i P_i^{\mathrm{net}} = \begin{cases} P_i^{\mathrm{net}} & \text{if } P_i^{\mathrm{net}} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{21}$$
$$\Leftrightarrow \alpha_i P_i^{\mathrm{net}} = \max\{P_i^{\mathrm{net}}, 0\} \tag{22}$$
$$\Leftrightarrow (1 - \alpha_i) P_i^{\mathrm{net}} = P_i^{\mathrm{net}} - \max\{P_i^{\mathrm{net}}, 0\} \tag{23}$$

Therefore, (17) and (18) can be rewritten as follows:

$$\mathrm{C_E^m} = \tau \sum_{i \in \mathrm{H^m}} \max\{P_i^{\mathrm{net}}, 0\} \mathrm{pr}_i \tag{24}$$
$$\mathrm{C_N^m} = \tau \sum_{i \in \mathrm{H^m}} (P_i^{\mathrm{net}} - \max\{P_i^{\mathrm{net}}, 0\}) \mathrm{pr}_i^{\mathrm{s}} \tag{25}$$

The problem now becomes a Linear Minimax problem which can be transformed to a Linear Programing problem [20] by replacing the max terms in the objective function by the representative variables together with the corresponding constraints:

- Representative variables:

$$P_{\mathrm{max}}^{\mathrm{m}} \text{ represents } \max_{i \in \mathrm{H^m}} \{P_i^{\mathrm{net}}\}$$
$$P_{\mathrm{pk}}^{\mathrm{m}} \text{ represents } \max_{j \in \mathrm{H_{pk}^m}} \{P_j^{\mathrm{net}}\}$$
$$P_{\mathrm{ppk}}^{\mathrm{m}} \text{ represents } \max_{k \in \mathrm{H_{ppk}^m}} \{P_k^{\mathrm{net}}\}$$
$$P_i^{+} \text{ represents } \max\{P_i^{\mathrm{net}}, 0\}$$

- Corresponding constraints:

$$P_i^{\mathrm{net}} \leq P_{\mathrm{max}}^{\mathrm{m}}, \forall i \in \mathrm{H^m} \tag{26}$$
$$P_j^{\mathrm{net}} \leq P_{\mathrm{pk}}^{\mathrm{m}}, \forall j \in \mathrm{H_{pk}^m} \tag{27}$$
$$P_k^{\mathrm{net}} \leq P_{\mathrm{ppk}}^{\mathrm{m}}, \forall k \in \mathrm{H_{ppk}^m} \tag{28}$$
$$P_i^{\mathrm{net}} \leq P_i^{+}, \forall i \in \mathrm{H^m} \tag{29}$$

III. Case Studies

In this section, case studies are conducted for a waste water treatment facility in New Mexico including: 1) TOU management without power factor correction; 2) TOU management with power factor correction. The hourly historical consumption data of the facility in 2016 is used. The peak demand power observed in this year is around $300kW$. A $100kW$ PV system is assumed and the hourly PV ouput data are generated using NREL's PVWatts [21]. The TOU rate structure is given as follows:

- Energy rate: $\text{pr} = 0.04537$ [$\$/kWh$]
- Peak-hour (6am-9pm) demand rate: $\text{d}_{\text{pk}} = 24.69$ [$\$/kWh$]
- Off-peak (9pm-6am) demand rate: $\text{d}_{\text{opk}} = 6.12$ [$\$/kWh$]
- Net-metering rate: $\text{pr}_{\text{s}} = 0.03[\$/kWh]$

The coefficients of loss functions in (5) and (6) are estimated based on experimental data given in [19]: $k^p = 3\%$ and $k^q = 4\%$. The optimization problems are formulated using Pyomo optimization modeling language [22]. Different sizes of energy storage are investigated. Charge and discharge efficiencies of the storage devices are assumed to be 95% in all cases. The state of charge of the ESS is maintained at 50% at the beginning of each month.

A. Case 1 - TOU management without power factor correction

The results are shown in Fig. 2 and Fig. 3. In Fig. 2, the graphs show the sensitivity of electricity cost to energy storage power and energy rating. The x-axis is the ESS's energy rating, the y-axis is the annual electricity cost, and each line represents one ESS's power rating. In this case, it is observed that the total annual cost at each ESS's power rating decreases as the energy rating increases. The rate of the decrease is high at first but significantly slowing down at the knee point of the curve. This is the point where energy arbitrage and peak shaving are limited by the power rating. The costs are bounded by the $200kW$ curve. This is because the maximum gap between peak load and valley load is around $200kW$. Any power ratings higher than the maximum gap do not increase the chance for peak shaving. Therefore, the optimum size can be found at $1000kWh$ (the knee point) of the 200kW curve. At this rating, the total saving is $\$30,290(16.8\%)$ in which $20,610(11.2\%)$ is contributed by the TOU management using ESS. As seen in Fig. 3, the peak demands during peak hours have been shifted to off-peak hours in order to reduce the demand charge. This happens in this case because the off-peak-hour demand price is much lower than the peak-hour demand price.

B. Case 2 - TOU management with power factor correction

In this case, the corrected power factor is set at 0.9. As seen in Fig. 4, the power factors are significantly smaller when the PV generation is high. The results show the ESS's inverter successfully maintain the power factor over 0.9 while charging and discharging for TOU management. Similar results for cost savings have been observed. With $1MWh/200kW$ ESS, the saving is about $\$1000$ more than in the previous case. This comes from the reduction in penalty for low power factor.

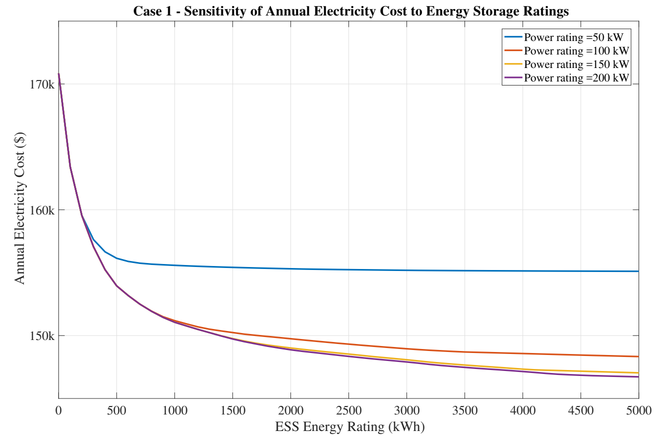

Fig. 2. Case 1 - Sensitivity of annual electricity bill to ESS size

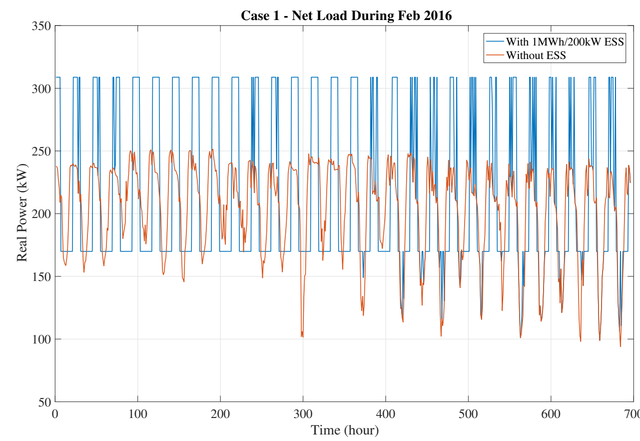

Fig. 3. Case 1 - Net load during Feb 2016

IV. Conclusions

In this paper, the benefits of behind-the-meter ESSs for TOU management with power factor correction have been studied. A MINLP is formulated to minimize the monthly electricity cost of the customer. The problem is then transformed to an LP problem using the Minimax technique. Case studies have been conducted for a waste water treatment facility. The results show energy storage can significantly reduce electricity cost by peak shaving. Using the proposed method, the inverter successfully maintains the power factor while charing and discharing the energy storage for TOU management. The sensitivity of annual electricity cost to ESS's sizes is also investigated. Future work in this area would consider the uncertainties of forecast errors as well as include a non-linear energy storage model in the optimization problem.

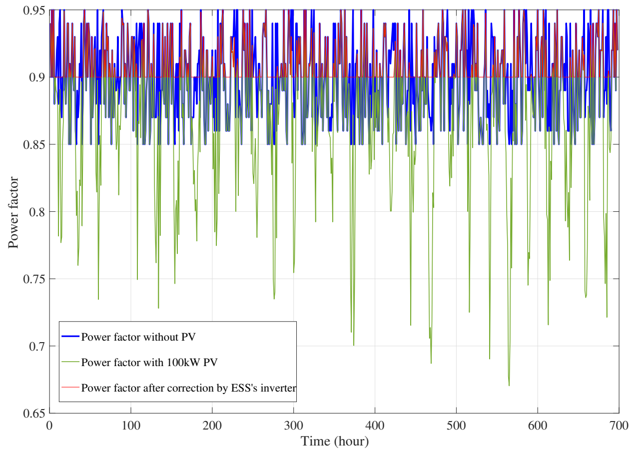

Fig. 4. Case 2 - Power factor correction using ESS's inverter

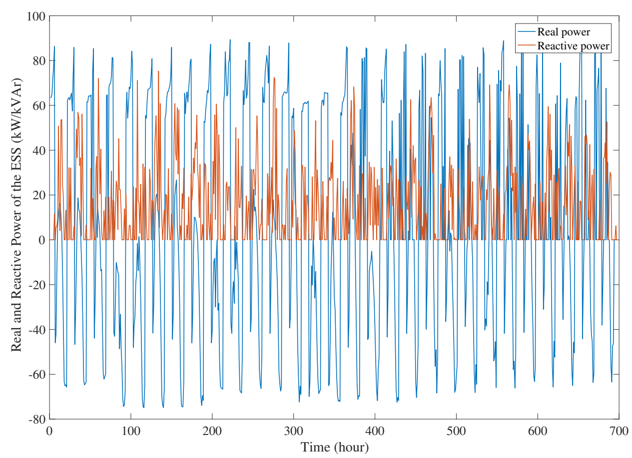

Fig. 5. Case 2 - Real and reactive power output of 200kW/1MWh ESS during Feb 2016

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