IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 16, 2022, accepted March 5, 2022, date of publication March 10, 2022, date of current version March 21, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3158303

MILP Optimized Management of Domestic PV-Battery Using Two Days-Ahead Forecasts

AMEENA SOROUR[1], MEGHDAD FAZELI[2], (Senior Member, IEEE), MOHAMMAD MONFARED[1], (Senior Member, IEEE), ASHRAF A. FAHMY[3,4], JUSTIN R. SEARLE[5], AND RICHARD P. LEWIS[5]

[1]Faculty of Science and Engineering, Swansea University, Swansea SA1 8EN, U.K.
[2]Energy Safety Research Institute (ESRI), Swansea University, Swansea SA1 8EN, U.K.
[3]ASTUTE, Swansea University, Swansea SA1 8EN, U.K.
[4]Department of Electrical Power and Machines, Helwan University, Helwan 11795, Egypt
[5]SPECIFIC-IKC, Swansea University, Swansea SA1 8EN, U.K.

Corresponding author: Ameena Sorour (970851@swansea.ac.uk)

This work was supported in part by the Qatar National Research Fund (a Member of Qatar Foundation) under Grant QRLP10-G-19022034, in part by the Sustainable Product Engineering Centre for Innovative Functional Industrial Coatings (SPECIFIC)-National Innovation and Knowledge Centre (IKC) through the Engineering and Physical Science Research Council under Grant EP/N020863/1, in part by the Innovate U.K. under Grant 920036, and in part by the Advanced Sustainable Manufacturing Technologies (Astute2020) Operation by the Supporting Manufacturing Companies Across Wales European Regional Development Fund through the Welsh Government and the Participating Higher Education Institutions under Grant c80892.

ABSTRACT This paper proposes an Energy Management System (EMS) for domestic PV-battery applications with the aim of reducing the absolute net energy exchange with the utility grid by utilizing the two days-ahead energy forecasts in the optimization process. A Mixed-Integer Linear Programming (MILP) exploits two days-ahead energy demand and PV generation forecasts to schedule the day-ahead battery energy exchange with both the utility grid and the PV generator. The proposed scheme is tested using the real data of the Active Office Building (AOB) located in Swansea University, UK. Performance comparisons with state-of-the-art and the commercial EMS currently running at the AOB reveal that the proposed EMS increases the self-consumption of PV energy and at the same time reduces the total energy cost. The absolute net energy exchange with the grid and the total operating costs are reduced by 121% and 54% compared to the state-of-the-art and 194% and 8% when compared to the commercial EMS over a six-month period. Furthermore, the results show that the proposed method can reduce the energy bill by up to 46% for the same period compared to the state-of-the-art. The paper also investigates the effect of using different objective functions on the performance of the EMS and shows that the proposed EMS operate more efficiently when it is compared with another cost function that directly promotes reducing the absolute net energy exchange.

INDEX TERMS Battery storage, energy management system, energy tariffs, forecast, mixed-integer linear programming, PV.

NOMENCLATURE

$P_B(t)$	Battery discharge/charge power (kW).
$P_{B\text{-}rating}$	Maximum battery discharge/charge power (kW).
$P_B{}^{disch}(t)$	Battery discharge power (kW).
$P_B{}^{charg}(t)$	Battery charge power (kW).
$P_{PV-1}(t)$	Forecasted PV generation for day1 (kW).
$P_{L-1}(t)$	Forecasted load demand for day1 (kW).
$P_{PV-2}(t)$	Forecasted PV generation for day2 (kW).
$P_{L-2}(t)$	Forecasted load demand for day2 (kW).
$SOC(t)$	Battery state of charge (%).
$E_{Day\text{-}f}$	Day-2 peak time energy forecast (kWh).
SOC_{max}	Maximum limit of the state of charge (%).
SOC_{min}	Minimum limit of the state of charge (%).
$E(t)$	Energy stored in the battery at time t (kWh).
$E(t-1)$	Energy stored in the battery at time t − 1 (kWh).
$P_G(t)$	Power exchange with the utility grid (kW).
$P_G{}^{max\text{-}export}$	Maximum limit exported power to the utility grid (kW).

The associate editor coordinating the review of this manuscript and approving it for publication was Behnam Mohammadi-Ivatloo.

$P_G^{max\text{-}import}$	Maximum limit imported power from the utility grid (kW).
$P_G^{export}(t)$	Exported power to the utility grid (kW).
$P_G^{import}(t)$	Imported power from the utility grid (kW).
$\Phi_{export}(t)$	Binary variable to indicate the building is exporting power to the utility grid.
$\Phi_{import}(t)$	Binary variable to indicate the building is importing power from the utility grid.
$\Phi_{B\text{-}disch}(t)$	Binary variable to indicate battery is discharging.
$\Phi_{B\text{-}charg}(t)$	Binary variable to indicate battery is charging.
$B_{capacity}(t)$	Battery capacity (kWh).
N_{cycle}	Battery cycle life.
CC_B	Capital cost of the battery (£).
C_{BSS}	Battery degradation cost (£).
C_{buy}	Price of imported energy from the utility grid (£/kWh).
C_{sell}	Price of exported energy to the utility grid (£/kWh).
$f_{sell}(t)$	Tariff for selling energy to the utility grid (£/kWh).
$f_{buy}(t)$	Tariff for buying energy from the utility grid (£/kWh).
C_{bill}	Bill cost (£).
C_F	Optimization cost function (£).
ΔT	Sample time (hr).
t_0	The time of the day starts at 12 AM.
T	The time of the day ends after 24 hours.
t	Current time (hr).
η_{conv}	Battery DC/DC converter efficiency (%).
η_c	Battery charging efficiency (%).
η_d	Battery discharging efficiency (%).
E_{import}	Imported energy from the utility grid (kWh).
E_{export}	Exported energy to the utility grid (kWh).

I. INTRODUCTION

Decarbonization and limited resources of fossil fuels (used in conventional power generation plants) have increased the demand for integrating Renewable Energy Sources (RESs) such as PV systems, especially for domestic applications [1]. Historically, Feed-in-Tariff (FIT) initiatives were introduced in several regions for small-scale-based RESs connected to the utility grid. However, high penetration of RESs, especially at the distribution level (where conventionally only consumption occurred), has created numerous challenges for the network operators [2]. As a result, in several countries like the UK, incentives are already reduced, encouraging a self-consumption approach. For example, the generation tariff (part of the FIT) in the UK has reduced from more than 54 p/kWh in 2010 to 3.79 p/kWh in 2019 [3], when the FIT has been replaced by the Smart Export Guarantee (SEG) scheme. The SEG requires some electricity suppliers to pay small-scale generators between 2 p/kWh and 5.6 p/kWh for their low-carbon electricity which they export to the grid [4]. It is noted that the SEG rates in the UK are currently less than the electricity purchasing prices. In addition, many countries such as the UK and Germany have already enforced some other measures to limit the surplus PV energy injection to the utility grid to encourage the self-consumption approach [5]. The main characteristic of this new trend is the minimization of the net energy exchange between the prosumer (producer + consumer) and the grid [6].

An effective self-consumption approach benefits from some sort of Battery Storage Systems (BSSs) and an intelligent Energy Management System (EMS). Based on previous literature, decision-making at the energy management level can be achieved either heuristically, such as rule-based-EMS [7], [8] or non-heuristically using optimization methods [1]. In terms of implementation, EMSs can be either online [7] or offline [1]. Also, different objectives can be defined as the main priority for EMSs, e.g., several works focused on reducing the energy bill using the BSS scheduling [9], while some other works proposed EMSs that schedule domestic appliances based on their priority and time of the day [8], [10], [11]. Authors in [12] proposed EMS based on a user priority list that can achieve savings of up to 87%. Similarly, authors in [13], [14] proposed an optimal load scheduling to reduce energy costs and peak loads. However, controlling the local loads approach is not preferable for some clients as it may affect their comfort.

There are various control algorithms in the literature proposed for EMSs. For example, the authors in [15] proposed a rule-based controller for real-time price-based EMS. Their work considered emergency load curtailment and vehicle-to-home support during interruption events. Authors in [16] and [17] proposed a rule-based EMS to maintain the power balance in the Micro-grid (MG) and reduce the bill. Similarly, authors in [7], [18], [19] proposed a Fuzzy Logic (FL)-based-EMS to minimize the energy cost. Although FL controllers and rule-based approaches can successfully deal with the MG components' nonlinearities and avoid complex mathematical modeling, they rely on the designer's justified rules, which may not be comprehensive in all aspects.

Authors in [20] proposed domestic EMS based on genetic harmony search algorithm to reduce the operating costs. However, their proposed system did not include the BSS. In [21] the proposed domestic EMS was applied to reduce the operating costs, while their system limited the BSS to store 30% of RES energy during the daytime. This limit deteriorates the PV local utilization and increases the imported energy from the grid.

In previous works, little consideration is given to the impact of the battery State of Health (SOH) during its operational lifetime as an effective factor in the EMSs. To overcome this shortage, authors in [22] and [23] limited the battery State of Charge (SOC) to 50% at the cost of increased capital costs and undermining PV self-consumption. Moreover, this simple approach while beneficial for battery health, it underutilizes the battery capacity. An alternative solution is to include battery degradation cost as an indication of the SOH of the battery [1], [24], [25].

Authors in [26] proposed an EMS for islanded MGs. The main target of their proposed method was to reduce the BSS degradation and improve the utilization of RESs. Authors in [27] proposed a centralized MG controller to reduce the conversion losses and the energy cost in the residential distribution system. In [28], Linear Programming (LP) was used for BSS scheduling, where the method is reported to achieve a high reduction in energy cost and greenhouse gases emission compared to the case where loads were only supplied by the grid. Authors in [29] considered the operational and maintenance cost of the solar units and the BSS in the objective function. Authors in [26]–[29] considered one day-ahead energy forecast in the optimization to achieve optimal day-ahead battery operation. However, their methods do not utilize the knowledge of the following day (day-2) energy forecasts which may cause unnecessary energy exchange with the grid. For example, the lack of knowledge of day-2 will result in exporting the available RES surplus energy to the utility grid rather than storing that energy in the BSS. Therefore, if on the next day (i.e. day-2), the PV generation is less than the load, the exchange energy with the utility grid and the energy bill will unnecessarily increase.

Several studies have been conducted using computational intelligence methods to solve the EMS optimization problems, such as Ant Colony optimization [30], Grey Wolf optimization [10], and Particle Swarm Optimization (PSO) [31].

While many studies focused on proposing different forecasting algorithms [5], there are significantly fewer published works identifying how best to utilize and integrate the forecasted data into an EMS. This study does not utilize a specific forecast method but approximates the forecasted data by imposing normally distributed random numbers on the historical data [32]. The main objective of this paper is to minimize the energy bill while the net exchanged energy with the utility grid is reduced through exploiting the two days-ahead energy forecasts in the adaptive optimization process. This reduces the distribution and transmission losses and grid voltage rise by enhancing the self-consumption of PV energy. The Active Office Building (AOB) located in Swansea University, is used as a case study to demonstrate the developed EMS. The proposed model equations are solved using the Mixed-Integer Linear Programming (MILP) optimization method and Gurobi® optimizer in MATLAB. The key contributions of this work can be summarised as follows:

a) Making better use of the BSS by including the two days-ahead forecasts in the EMS.
b) Proposing an EMS using the MILP optimization method such that:
   i. it reduces the absolute net energy exchange with the grid, which in turn reduces the burdens on the utility grid and the losses;
   ii. it reduces the overall electricity bill;
   iii. it reduces the overall operating costs of the system by considering the capital and the degradation costs of the BSS in the EMS.

The rest of the paper is organized as follows. Section II describes the system configuration, section III introduces the proposed EMS. Section IV presents the problem formulation, and section V presents the simulation results and discussion. Finally, the conclusions of this work are presented in section VI.

II. SYSTEM CONFIGURATION

Fig.1 illustrates the AOB system configuration, which consists of a 22.3 kWp PV system and a 110.4 kWh lithium-ion BSS linked to the 48 V-DC bus. The PV DC-DC converter rating is 23.2 kW. Three single-phase inverters of 230 V-AC, 48 V-DC, and 15 kVA each are employed. The maximum load demand is 32.5 kW, and the rated charge/discharge power ($P_{B\text{-}rating}$) of the BSS is 102.4 kW [33]. Moreover, the maximum SOC (SOC_{max}) and the minimum SOC (SOC_{min}) limits are set to 98% and 20%, respectively [7].

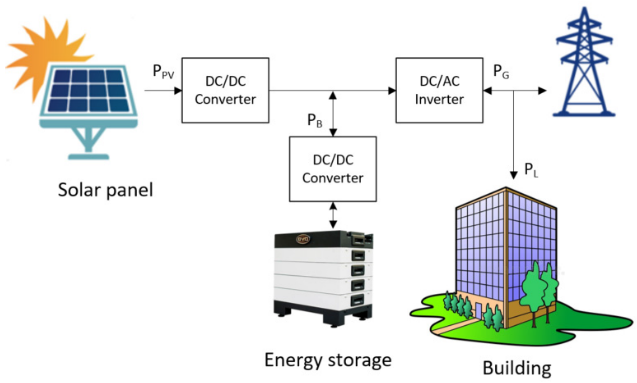


FIGURE 1. Schematic diagram of the Active Office Building.

III. PROPOSED ENERGY MANAGEMENT SYSTEM

The proposed EMS aims to minimize the absolute net energy exchanged with the utility grid to enhance PV self-consumption while reducing the overall operational costs.

The proposed EMS method follows the procedures shown in Fig. 2, and detailed in the below steps:

- first, the EMS asks for the initial SOC of the BSS.
- then the two days-ahead forecasted data are requested: day-1 PV generation (P_{PV-1}), day-2 PV generation (P_{PV-2}), day-1 load demand (P_{L-1}), and day-2 load demand (P_{L-2}).
- then the EMS calculates the peak time energy forecast ($E_{Day\text{-}f}$) from day-2 forecasted data as shown in (1):

$$E_{Day\text{-}f} = \int_{t=8\,\mathrm{AM}}^{t=8\,\mathrm{PM}} (P_{PV-2}(t) - P_{L-2}(t))\,dt \tag{1}$$

- the MILP optimization is then performed for one day-ahead (i.e., day-1) to obtain the BSS scheduling.

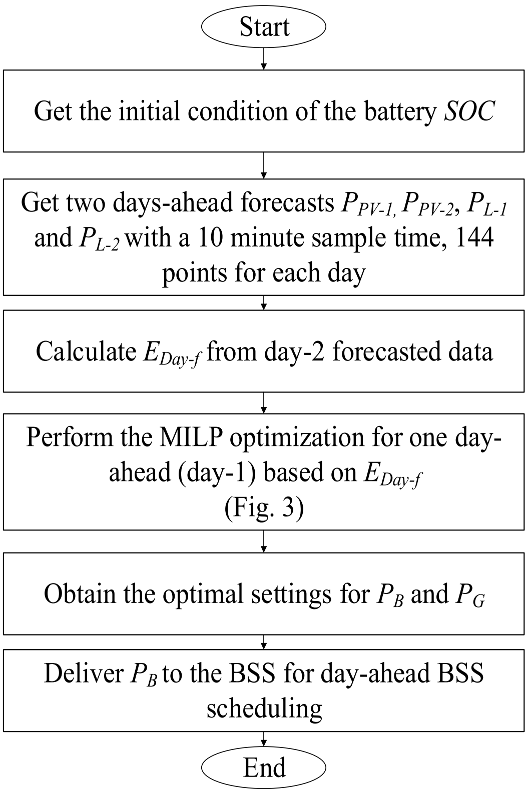


FIGURE 2. Flowchart of the proposed EMS based on two days-ahead forecasts.

- finally, the EMS gets the decision variables, i.e., the utility grid power (P_G) and battery power (P_B), and send the signal to the BSS.

IV. PROBLEM FORMULATION

The objective function focuses on minimizing the absolute net energy exchange with the utility grid while considering the energy cost. The problem is formulated using MILP optimization. The algorithm aims to minimize the cost function (C_F), which includes the price of energy imported from the utility grid (C_{buy}), price of energy exported to the utility grid (C_{sell}) and the BSS degradation cost (C_{BSS}).

$$C_F = |C_{buy}| + |C_{sell}| + C_{BSS} \tag{2}$$

It is worth noting that the C_F considers the C_{buy} and C_{sell} as absolute values to reduce the net exchanged energy with the utility grid (i.e. reducing the total energy transactions). In addition, the C_{BSS} is included in the cost function to consider the battery lifetime. The bill cost (C_{bill}) is calculated by subtracting the C_{sell} from C_{buy} (note that C_{sell} is a negative value):

$$C_{bill} = C_{buy} + C_{sell} \tag{3}$$

The surplus PV energy is exported to the utility grid after supplying the load and charging the BSS. The selling and purchasing energy costs are calculated as [1]:

$$C_{buy} = \sum\nolimits_{t_0}^{T} \Delta T \times f_{buy}(t) \times P_G(t), \quad P_G(t) > 0 \tag{4}$$

$$C_{sell} = \sum\nolimits_{t_0}^{T} \Delta T \times f_{sell}(t) \times P_G(t), \quad P_G(t) < 0 \tag{5}$$

where the t_0 is the start time of the day, 12 AM, T is 24 hours, ΔT (hr) is the sampling period of ten minutes, $f_{buy}(t)$ is the purchasing tariff from the utility grid (£/kWh), $f_{sell}(t)$ is the feed-in tariff (£/kWh) to the utility grid.

Equation (6) represents the power balance equation of the system:

$$P_{L-1}(t) - P_{PV-1}(t) = P_G(t) + P_B(t) \tag{6}$$

A. BATTERY MODEL

The BSS model is established as follows. The degradation cost of each charging/discharging cycle is represented as in (7) [1]:

$$C_{BSS} = \sum\nolimits_{t_0}^{T} \frac{CC_B \times \eta_{Conv} \times \eta_c \times \Delta T \times P_B{}^{charg}(t)}{2 \times N_{cycle}} + \frac{CC_B \times \Delta T \times P_B{}^{disch}(t)}{\eta_{Conv} \times \eta_d \times 2 \times N_{cycle}} \tag{7}$$

where the CC_B represents the capital cost of the battery (£) (not including the power converters), N_{cycle} is the number of life cycles of the battery, η_{conv} is the battery DC/DC converter efficiency (%), $P_B{}^{disch}$ is the battery discharge power (kW), $P_B{}^{charg}$ is the battery charge power (kW), η_d and η_c are the battery discharging and charging efficiencies (%). Note that $P_B{}^{charg}$ is a negative value and $P_B{}^{disch}$ is a positive value.

The stored energy in the BSS and the SOC of the battery can be estimated as [1]:

$$E(t) = E(t-1) - \frac{\Delta T \times P_B{}^{disch}(t)}{\eta_d} - \Delta T \times \eta_c \times P_B{}^{charg}(t) \tag{8}$$

$$SOC(t) = \frac{E(t)}{B_{capacity(t)}} \times 100 \tag{9}$$

where $E(t)$ and $E(t-1)$ are the energy stored in the battery at time t and $t-1$, respectively, and $B_{capacity}$ is the battery capacity.

The BSS settings of the day-ahead depend on whether it is peak or off-peak time. During the peak times, the battery is allowed to be discharged to its minimum limits (i.e., SOC_{min}) to avoid purchasing unnecessary energy at a high price tariff from the utility grid. The SOC is limited to its allowable limits during peak times as given by (10):

$$SOC_{min} \le SOC(t) \le SOC_{max} \tag{10}$$

During the off-peak times, the proposed algorithm considers day-2 forecast needs (i.e., $E_{Day\text{-}f}$), therefore (11) is used to ensure that the predicted required energy needed for day-2 peak time is stored in the BSS during the off-peak times:

$$SOC_{min} + (100 \times \frac{E_{Day\text{-}f}}{B_{capacity}}) \le SOC(t) \le SOC_{max} \tag{11}$$

Equation (12) is used to calculate the instantaneous power exchange with the battery for analysis purposes [1]:

$$P_B(t) = {P_B}^{disch}(t) \times \eta_{Conv} + \frac{{P_B}^{charg}(t)}{\eta_{Conv}} \tag{12}$$

The instantaneous battery power is limited to the maximum allowable charge/discharge rating of the battery as follows [1]:

$$0 \le {P_B}^{disch}(t) \le P_{B\text{-}rating} \tag{13}$$

$$-P_{B\text{-}rating} \le {P_B}^{charg}(t) \le 0 \tag{14}$$

B. SYSTEM CONSTRAINT

In this part, four binary variables are created as state flags transition indications for the battery and utility grid. The four binary variables are $\Phi_{B\text{-}disch}$, $\Phi_{B\text{-}charg}$, Φ_{import} and Φ_{export}. The $\Phi_{B\text{-}disch}$, $\Phi_{B\text{-}charg}$ are binary variables for battery discharge and charge modes, respectively. The Φ_{import} and Φ_{export} are binary variables for import from the utility grid and export to the utility grid, respectively.

The binary variables $\Phi_{B\text{-}disch}$ and $\Phi_{B\text{-}charg}$ are used to ensure that the battery is either charging or discharging at any time instant by using constraints (15) to (17) [1]:

$$\Phi_{B\text{-}disch}(t) + \Phi_{B\text{-}charg}(t) \le 1 \tag{15}$$

$$\Phi_{B\text{-}disch}(t) = \begin{cases} 1, & P_B(t) > 0 \\ 0, & P_B(t) < 0 \end{cases} \tag{16}$$

$$\Phi_{B\text{-}charg}(t) = \begin{cases} 1, & P_B(t) < 0 \\ 0, & P_B(\mathrm{t}) > 0 \end{cases} \tag{17}$$

where $\Phi_{B\text{-}disch}(t)$ equals 1 indicate that the battery is discharging, $\Phi_{B\text{-}charg}(t)$ equals 1 indicate that the battery is charging.

Constraints (18) and (19) are used to link between the battery power and the binary variables [1]:

$${P_B}^{disch}(t) \le \Phi_{B\text{-}disch}(t) \times (P_{B\text{-}rating}) \tag{18}$$

$${P_B}^{charg}(t) \le \Phi_{B\text{-}charg}(t) \times (-P_{B\text{-}rating}) \tag{19}$$

The binary variables of $\Phi_{import}(t)$ and $\Phi_{export}(t)$ ensure the building is only either importing or exporting power at any time instant using the constraints (20) - (23) are [1]:

$$\Phi_{import}(t) + \Phi_{export}(t) \le 1 \tag{20}$$

$${P_G}^{import}(t) \le \Phi_{import}(t) \times {P_G}^{max\text{-}import} \tag{21}$$

$${P_G}^{export}(t) \le \Phi_{export}(t) \times {P_G}^{max\text{-}export} \tag{22}$$

$$P_G(t) = {P_G}^{import}(t) - {P_G}^{export}(t) \tag{23}$$

$\Phi_{import}(t)$ equals 1 if the building is importing power from the utility grid and equals 0 otherwise, and $\Phi_{export}(t)$ equals 1 if the building is exporting power to the utility grid and equals 0 otherwise. ${P_G}^{import}(t)$ is the imported power from the utility grid, ${P_G}^{export}(t)$ is the exported power to the utility grid, while ${P_G}^{max\text{-}import}$ / ${P_G}^{max\text{-}export}$ are the limits for the imported/exported powers from /to the utility grid.

To avoid discharging from the battery at the same time when the building is exporting its excess PV power to the utility grid, (24) is used [1]:

$$\Phi_{B\text{-}disch}(t) + \Phi_{export}(t) \le 1 \tag{24}$$

where $\Phi_{B\text{-}disch}(t)$ equals 1 if the battery is discharging and equals 0 otherwise, $\Phi_{export}(t)$ equals 1 if the building exports power to the utility grid and equals 0 otherwise.

C. MIXED-INTEGER LINEAR PROGRAMMING

In this work, the MILP optimization technique and Gurobi® Optimizer tool are used to solve the optimization problem in the MATLAB environment. The MILP is a mathematical optimization technique used to find the best solution for the objective function based on a set of constraints and variables [34], [35]. MILP problem can be solved by three different approaches, namely, Branch and Bound, Cutting Plane and Feasibility Pump. This study uses the Branch and Bound algorithm (also known as Tree search) [36]. The algorithm starts with the original MILP problem without the limitations, which is called the relaxation of the original LP problem. The Tree search algorithm is divided into three main steps: (1) branching stage, where a variable is picked and the problem is divided into two sub problems at this variable, (2) bounding stage, which solves the relaxed LP to find the best possible objective value for the node, (3) pruning stage, where if the subproblem is infeasible, the tree will not develop any further [37]. The flowchart in Fig. 3 illustrates how the optimization process is performed and how the constraints are met. As shown in Fig. 3, in order to find the optimal day-ahead setting for the BSS based on $E_{Day\text{-}f}$, the cost function in (2) is optimized by these three steps. Firstly, the solution of the problem is obtained without any constraints (i.e., the relaxed LP). Secondly, the constraints are applied over the obtained results and the infeasible ones are removed. Finally, the variables which generate a feasible solution are used to generate more variables and then another iteration will be taken to solve the problem with those variables until the optimal solution is obtained. The feasible solution is a solution that meets all constraints, and the optimal solution is obtained when the best objective function value is achieved.

V. RESULTS AND DISCUSSION

In this section, the performance of the proposed EMS is compared with a recently published work [1] and the EMS that is currently used in the AOB. Especially, the operating costs and absolute net energy exchanged with the utility grid are compared to highlight the benefits of the proposed method. The algorithm in Fig. 2 is run for each day of the six months (from May to October 2019) with a sample time (ΔT) of ten minutes.

There are several approaches to predict PV generation and load consumption, such as Artificial Neural Network [38], Differential Evolution [39] and PSO [40]. For the sake of generality, this study does not use a specific forecast method.

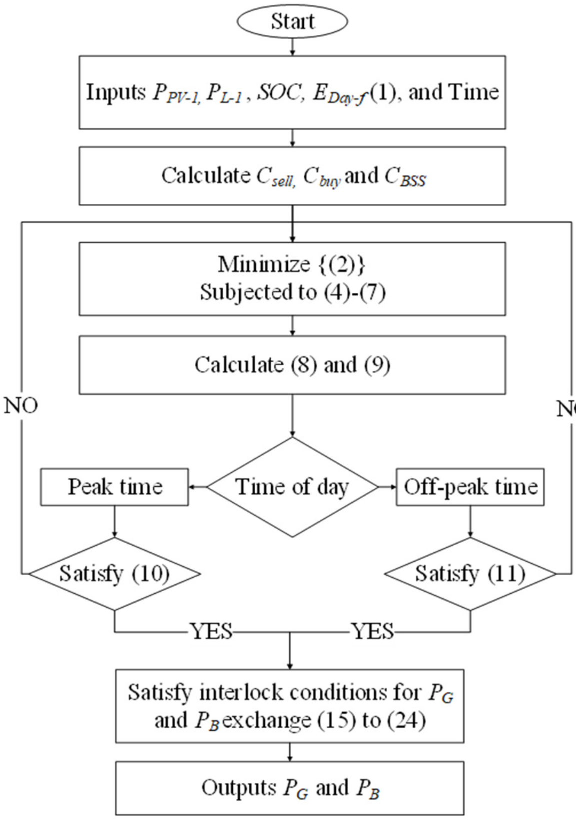


FIGURE 3. Flowchart of the MILP optimization process.

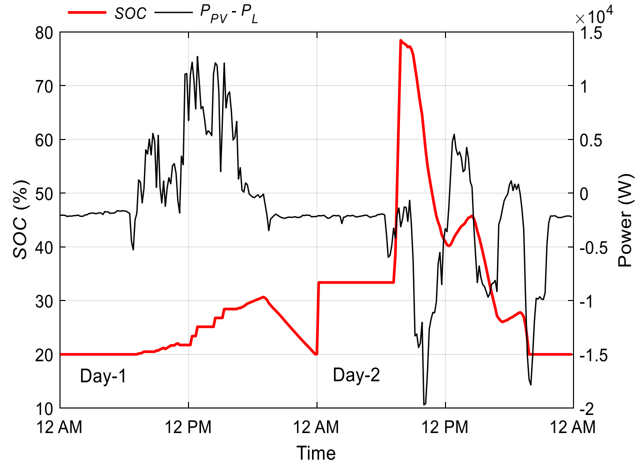


FIGURE 4. Two test days (23rd and 24th of May 2019) for the EMS in [1]. The red and black colors represent *SOC* and P_{PV} - P_L, respectively.

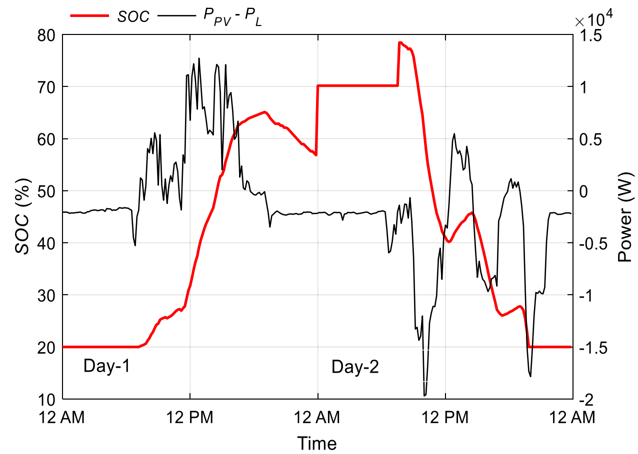


FIGURE 5. Two test days (23rd and 24th of May 2019) for the proposed EMS. The red and black colors represent *SOC* and P_{PV} - P_L, respectively.

Instead, the forecast error is accounted for by imposing normally distributed random numbers on the historical data [32]. The Mean Absolute Percentage Error (MAPE) of forecasted energy is assumed to be 30% over the six months.

In this study, two different tariff rates are considered according to the electricity utility company in the UK [41]. The peak rate applies from 8:00 AM to 8:00 PM, while the off-peak tariff rate is applied for the rest of the day. The tariff prices for the peak and off-peak are £0.1666/kWh and £0.1104/kWh, respectively. The PV export price is £0.055/kWh [4].

Recently, lithium-ion battery price has been reduced significantly [42], [43]. In this study, the CC_B is 273£/kWh and the N_{cycle} is 6000 [44].

A. PERFORMANCE COMPARISON

Figs. 4 and 5 show the battery performance for the EMS in [1] and the proposed EMS, respectively, for two test days (23rd and 24th of May 2019). The red and black lines represent *SOC* and P_{PV} - P_L, respectively. Note that in day-1, the generation is higher than demand most of the time and in day-2, the demand is higher than the generation most of the time. Fig. 4 shows that the battery is not charged with the available PV surplus power. Instead, the surplus power is exported to the utility grid to reduce the operating cost as energy is not required during day-1. This is because [1] does not use day-2 forecast in the EMS. On day-2, the battery is charged during off-peak from the utility grid to supply the load during peak time. The main objective of the EMS in [1] is reducing the energy bill while considering C_{BSS}. The main drawback of this method is that the optimization algorithm does not consider the day-2 generation and consumption forecast. This will result in higher operating costs and an increase in the energy exchange with the utility grid. In addition, this method is feeding the PV surplus power into the utility grid rather than charging the battery to supply load on the next day.

Unlike the EMS in [1], in the proposed system the battery is charged by the PV surplus power to increase the PV local consumption since it has prior knowledge about day-2 forecast energy, as illustrated in Fig. 5. In addition, the battery discharges energy stored from PV to avoid purchasing energy from the utility grid during peak times. This process reduces the absolute net energy exchanged and avoids purchasing unnecessary energy from the utility grid, which maximizes the use of PV power while considering the battery degradation costs.

B. COMPARING ABSOLUTE NET ENERGY EXCHANGED AND OPERATIONAL COSTS

Fig. 6 shows the exported energy during peak time, for the six months. The blue, orange and yellow bars represent the proposed EMS in this work, the EMS adopted in [1] and the EMS currently in use in the AOB, respectively. As illustrated in Fig. 6, the proposed EMS enhances the PV self-consumption utilization by reducing the exported energy during peak time to the utility grid.

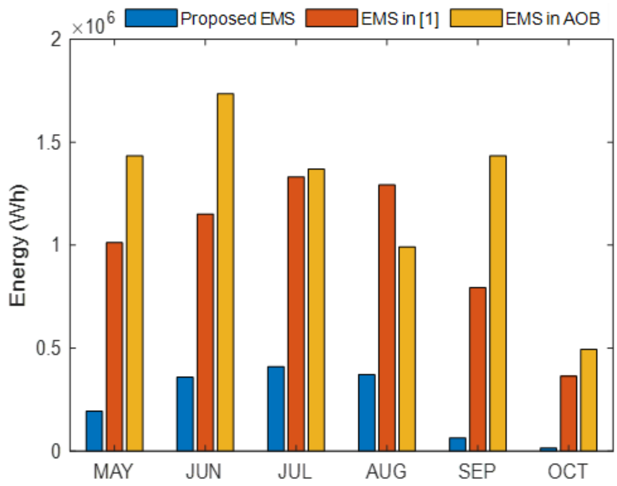


FIGURE 6. Exported energy during peak time. The blue, orange and yellow bars represent proposed EMS, EMS in [1] and EMS in AOB.

Figs. 7 and 8 show imported energies during peak and off-peak times, respectively. The blue, orange and yellow bars represent the proposed EMS in this work, the EMS adopted in [1] and the EMS currently in use in the AOB, respectively. As shown in Figs. 7 and 8, the proposed EMS reduces the imported energies compared to the proposed method in [1] and the EMS in the AOB.

Fig. 9 shows the total energy imported/exported from/to the utility grid for six months. The blue, orange and yellow bars represent the proposed EMS in this work, the EMS adopted in [1] and the EMS currently in use in the AOB, respectively, for six months. As shown in Fig. 9, the proposed EMS reduces the net energy exchanged with the utility grid as the absolute net energy exchanged is reduced by 121 % and 194%, compared to the EMS adopted in [1] and the EMS in the AOB, respectively.

Table 1 compares the total operating costs of the proposed EMS with the EMS adopted in [1] and the EMS currently in use in the AOB for the six months. The proposed method reduces the energy bill by 46% and 37 % compared to EMS adopted in [1] and the EMS in the AOB. The proposed EMS uses the battery more than the EMS of [1], which reflects in higher degradation cost as illustrated in Table 1. This is simply because the proposed algorithm aimed to enhance the

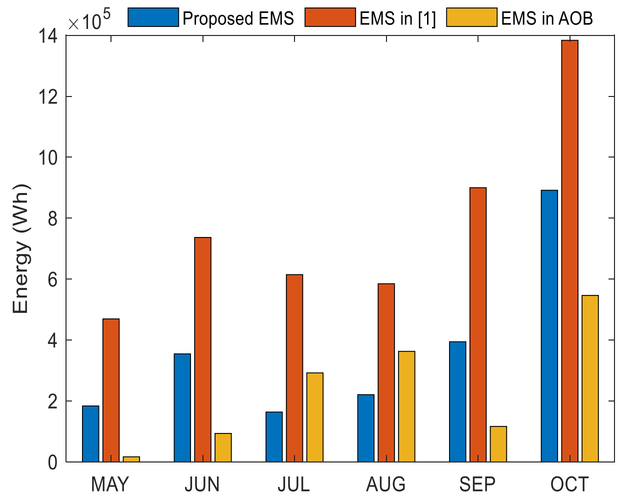


FIGURE 7. Imported energy during peak time. The blue, orange and yellow bars represent proposed EMS, EMS in [1] and EMS in AOB.

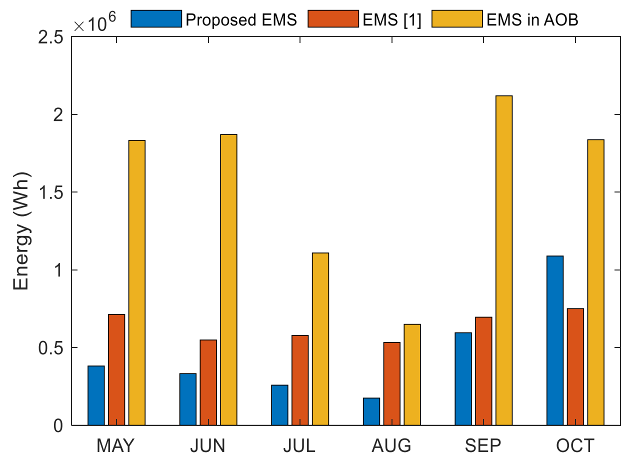


FIGURE 8. Imported energy during off-peak time. The blue, orange and yellow bars represent proposed EMS, EMS in [1] and EMS in AOB.

TABLE 1. Operating costs for six months.

Methods	Energy bill (£)	Degradation cost (£)	Total operating costs (£)
Proposed EMS	598	234	832
EMS in [1]	874	24	898
EMS in AOB	816	463	1279

self-consumption of PV power. In contrast, the energy bill in the proposed EMS is considerably less than that in [1], therefore, the battery degradation cost is covered from the energy bill saving. The proposed EMS reduces the total operating costs by 8% and 54% over six months compared to the EMS of [1] and the EMS of the AOB, respectively.

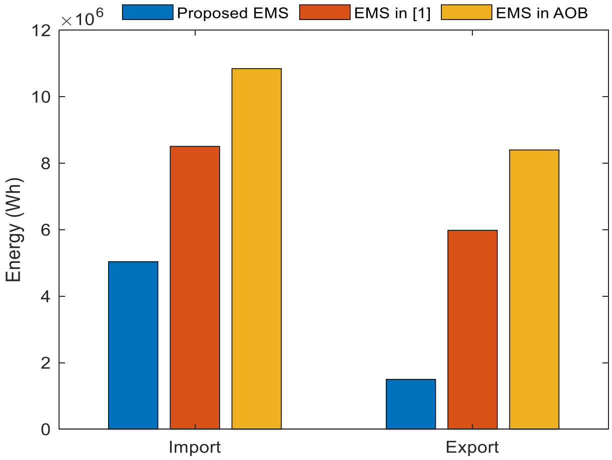


FIGURE 9. Total imported and exported energies for six-month period. The blue, orange and yellow bars represent proposed EMS, EMS in [1] and EMS in AOB.

C. COMPARING DIFFERENT COST FUNCTIONS

The main objective of the proposed cost function of (2) is to minimize the absolute net energy exchanged with the utility grid while reducing the energy bill by considering the tariff prices. From a network operator viewpoint, a minimized net energy exchange might be more favorable since it reduces (1) the transmission losses, (2) the required central generation/storage systems. In other words, a minimized energy exchange can be used as a measure of energy independence of a prosumer, which in future networks, with a very high penetration of distributed generations, might be a definitive factor. With this motivation in mind, this sub-section investigates the impacts of using the objective function of (25) on the performance of the proposed EMS:

$$C_F = |E_{import}| + |E_{export}| \tag{25}$$

where the E_{import} and E_{export} are the imported and exported energies from/to utility grid, respectively. Using the sum absolute values of the imported and exported energy as the cost function directly promotes reducing the net energy exchange, which is reflected in maximizing local consumption of the available RES. The results are compared in Table 2.

The results show that the cost function of (25) increases the energy bill by 7% compared to the cost function of (2). However, there is no difference in the absolute net energy exchanged when the cost function of (2) is compared with the cost function of (25). This demonstrates that the cost function of (2) can be considered as an optimal cost function that satisfies targets of minimizing the absolute net energy exchanged with the utility grid and the energy bill.

TABLE 2. Bill cost for six months.

Cost function	Energy bill (£)	Degradation cost (£)	Total operating costs (£)	Absolute net energy exchanged (Wh)
(2)	598	234	832	6.536×10^6
(25)	642	233	875	6.544×10^6

VI. CONCLUSION

The proposed EMS controls the battery effectively to (1) reduce the operating costs, (2) reduce the unnecessary energy exchange with the utility grid, (3) reduce the transmission losses, and the requirements for central generation systems. The proposed EMS can meet the demand during the peak tariff period by discharging the battery rather than importing from the utility grid through exploiting the next day-ahead forecast (i.e., day-2). The proposed algorithm reduces the daily energy costs and improves PV self-consumption by reducing energy exchange with the utility grid.

ACKNOWLEDGMENT

The authors would like to acknowledge QRLP10-G-19022034 from Qatar National Fund (a member of Qatar Foundation) for their financial support. In addition, SPECIFIC-IKC for providing the data from "Active Buildings" demonstrators, which made this project possible.

REFERENCES

[1] M. Elkazaz, M. Sumner, E. Naghiyev, S. Pholboon, R. Davies, and D. Thomas, "A hierarchical two-stage energy management for a home microgrid using model predictive and real-time controllers," *Appl. Energy*, vol. 269, Jul. 2020, Art. no. 115118.

[2] M. Fazeli, P. M. Holland, and M. Baruwa, "'Grid'-less power systems: A vision for future structure of power networks," *IEEE Access*, vol. 8, pp. 159120–159131, 2020.

[3] Which. (2021). *What was the Feed-in Tariff*. Accessed: Jan. 10, 2022. [Online]. Available: https://www.which.co.U.K./reviews/feed-in-tariffs/article/feed-in-tariffs/what-was-the-feed-in-tariff-aAsa36S95iJy

[4] GreenMatch. (2021). *Smart Export Guarantee*. Accessed: Jan. 1, 2022. [Online]. Available: https://www.greenmatch.co.U.K./green-energy/grants/smart-export-guarantee

[5] M. Monfared, M. Fazeli, R. Lewis, and J. Searle, "Fuzzy predictor with additive learning for very short-term PV power generation," *IEEE Access*, vol. 7, pp. 91183–91192, 2019.

[6] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins, "Peer-to-peer energy trading in a community microgrid," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2017, pp. 1–5.

[7] K. Mansiri, S. Sukchai, and C. Sirisamphanwong, "Fuzzy control algorithm for battery storage and demand side power management for economic operation of the smart grid system at Naresuan university, Thailand," *IEEE Access*, vol. 6, pp. 32440–32449, 2018.

[8] K. Parvin, M. A. Hannan, A. Q. Al-Shetwi, P. J. Ker, M. F. Roslan, and T. M. I. Mahlia, "Fuzzy based particle swarm optimization for modeling home appliances towards energy saving and cost reduction under demand response consideration," *IEEE Access*, vol. 8, pp. 210784–210799, 2020.

[9] M. Elkazaz, M. Sumner, R. Davies, S. Pholboon, and D. Thomas, "Optimization based real-time home energy management in the presence of renewable energy and battery energy storage," in *Proc. Int. Conf. Smart Energy Syst. Technol. (SEST)*, Sep. 2019, pp. 1–6.

[10] T. Molla, B. Khan, B. Moges, H. H. Alhelou, R. Zamani, and P. Siano, "Integrated optimization of smart home appliances with cost-effective energy management system," *CSEE J. Power Energy Syst.*, vol. 5, no. 2, pp. 249–258, 2019.

[11] V. Hosseinnezhad, M. Shafie-Khah, P. Siano, and J. P. S. Catalao, "An optimal home energy management paradigm with an adaptive neuro-fuzzy regulation," *IEEE Access*, vol. 8, pp. 19614–19628, 2020.

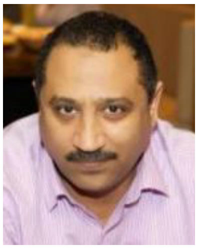
[12] S. A. Nabavi, N. H. Motlagh, M. A. Zaidan, A. Aslani, and B. Zakeri, "Deep learning in energy modeling: Application in smart buildings with distributed energy generation," *IEEE Access*, vol. 9, pp. 125439–125461, 2021.
[13] M. A. Rahman, I. Rahman, and N. Mohammad, "Demand side residential load management system for minimizing energy consumption cost and reducing peak demand in smart grid," in *Proc. 2nd Int. Conf. Adv. Inf. Commun. Technol. (ICAICT)*, Nov. 2020, pp. 376–381.
[14] A. Nawaz, G. Hafeez, I. Khan, K. U. Jan, H. Li, S. A. Khan, and Z. Wadud, "An intelligent integrated approach for efficient demand side management with forecaster and advanced metering infrastructure frameworks in smart grid," *IEEE Access*, vol. 8, pp. 132551–132581, 2020.
[15] A. Sangswang and M. Konghirun, "Optimal strategies in home energy management system integrating solar power, energy storage, and vehicle-to-grid for grid support and energy efficiency," *IEEE Trans. Ind. Appl.*, vol. 56, no. 5, pp. 5716–5728, Sep. 2020.
[16] P. S. Kumar, R. P. S. Chandrasena, V. Ramu, G. N. Srinivas, and K. V. S. M. Babu, "Energy management system for small scale hybrid wind solar battery based microgrid," *IEEE Access*, vol. 8, pp. 8336–8345, 2020.
[17] S. C. Teja and P. K. Yemula, "Energy management of grid connected rooftop solar system with battery storage," in *Proc. IEEE Innov. Smart Grid Technol. Asia (ISGT-Asia)*, Nov. 2016, pp. 1195–1200.
[18] R. Zhang, S. VE, and R. D. J. Samuel, "Fuzzy efficient energy smart home management system for renewable energy resources," *Sustainability*, vol. 12, no. 8, p. 3115, Apr. 2020.
[19] M. Jafari, Z. Malekjamshidi, J. Zhu, and M.-H. Khooban, "A novel predictive fuzzy logic-based energy management system for grid-connected and off-grid operation of residential smart microgrids," *IEEE J. Emerg. Sel. Topics Power Electron.*, vol. 8, no. 2, pp. 1391–1404, Jun. 2020.
[20] H. Hussain, N. Javaid, S. Iqbal, Q. Hasan, K. Aurangzeb, and M. Alhussein, "An efficient demand side management system with a new optimized home energy management controller in smart grid," *Energies*, vol. 11, no. 1, p. 190, Jan. 2018.
[21] A. Ahmad, A. Khan, N. Javaid, H. M. Hussain, W. Abdul, A. Almogren, A. Alamri, and I. A. Niaz, "An optimized home energy management system with integrated renewable energy and storage resources," *Energies*, vol. 10, no. 4, p. 549, Apr. 2017.
[22] M. F. M. Yusof and A. Z. Ahmad, "Power energy management strategy of micro-grid system," in *Proc. IEEE Int. Conf. Automat. Control Intell. Syst. (ICACIS)*, Oct. 2016, pp. 107–112.
[23] J. C. Pena-Aguirre, A.-I. Barranco-Gutierrez, J. A. Padilla-Medina, A. Espinosa-Calderon, and F. J. Perez-Pinal, "Fuzzy logic power management strategy for a residential DC-microgrid," *IEEE Access*, vol. 8, pp. 116733–116743, 2020.
[24] F. Li, C. Canizares, and Z. Lin, "Energy management system for DC microgrids considering battery degradation," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Aug. 2020, pp. 1–5.
[25] C. Ju and P. Wang, "Energy management system for microgrids including batteries with degradation costs," in *Proc. IEEE Int. Conf. Power Syst. Technol. (POWERCON)*, Sep. 2016, pp. 1–6.
[26] U. R. Nair and R. Costa-Castello, "A model predictive control-based energy management scheme for hybrid storage system in islanded microgrids," *IEEE Access*, vol. 8, pp. 97809–97822, 2020.
[27] S. Gangatharan, M. Rengasamy, R. M. Elavarasan, N. Das, E. Hossain, and V. M. Sundaram, "A novel battery supported energy management system for the effective handling of feeble power in hybrid microgrid environment," *IEEE Access*, vol. 8, pp. 217391–217415, 2020.
[28] H. A. Muqeet, I. A. Sajjad, A. Ahmad, M. M. Iqbal, S. Ali, and J. M. Guerrero, "Optimal operation of energy storage system for a prosumer microgrid considering economical and environmental effects," in *Proc. Int. Symp. Recent Adv. Electr. Eng. (RAEE)*, Aug. 2019, pp. 1–6.
[29] U. B. Tayab, F. Yang, M. El-Hendawi, and J. Lu, "Energy management system for a grid-connected microgrid with photovoltaic and battery energy storage system," in *Proc. Austral. New Zealand Control Conf. (ANZCC)*, Dec. 2018, pp. 141–144.
[30] S. Rahim, Z. Iqbal, N. Shaheen, Z. A. Khan, U. Qasim, S. A. Khan, and N. Javaid, "Ant colony optimization based energy management controller for smart grid," in *Proc. IEEE 30th Int. Conf. Adv. Inf. Netw. Appl. (AINA)*, Mar. 2016, pp. 1154–1159.
[31] H. T. Dinh, J. Yun, D. M. Kim, K. Lee, and D. Kim, "A home energy management system with renewable energy and energy storage utilizing main grid and electricity selling," *IEEE Access*, vol. 8, pp. 49436–49450, 2020.
[32] X. Yan, D. Abbes, and B. Francois, "Uncertainty analysis for day ahead power reserve quantification in an urban microgrid including PV generators," *Renew. Energy*, vol. 106, pp. 288–297, Jun. 2017.
[33] DYB. (2018). *BYD BATTERY-BOX*. Accessed: Nov. 10, 2021. [Online]. Available: https://www.originenergy.com.au/content/dam/origin/residential/solar/byd-battery-box-brochure-2018.pdf
[34] M. Jünger, T. M. Liebling, D. Naddef, G. L. Nemhauser, W. R. Pulleyblank, G. Reinelt, G. Rinaldi, and L. A. Wolsey, Eds., *50 Years of Integer Programming 1958–2008: From the Early Years to the State-of-the-Art*. Springer, 2009. [Online]. Available: https://books.google.co.uk/books?hl=en&lr=&id=bUJc_weiYfkC&oi=fnd&pg=PR5&dq=50+Years+of+Integer+Programming+597+1958%3F2008:&ots=0zEUMmsmLT&sig=WF6McR9OYG1UoXa26pe0-kyWAS8#v=onepage&q=50%20Years%20of%20Integer%20Programming%20597%201958%3F2008%3A&f=false
[35] J. P. Vielma, "Mixed integer linear programming formulation techniques," *SIAM Rev.*, vol. 57, no. 1, pp. 3–57, 2015.
[36] *Gurobi*. (2021). Accessed: Oct. 14, 2021. [Online]. Available: https://www.gurobi.com/resource/mip-basics/
[37] J. C. Smith and Z. C. Taskin, "A tutorial guide to mixed-integer programming models and solution techniques," *Optim. Med. Biol.*, pp. 521–548, Jan. 2008, doi: 10.1201/9780849305696.axa.
[38] M. S. Hossain and H. Mahmood, "Short-term photovoltaic power forecasting using an LSTM neural network and synthetic weather forecast," *IEEE Access*, vol. 8, pp. 172524–172533, 2020.
[39] M. Seyedmahmoudian, E. Jamei, G. Thirunavukkarasu, T. Soon, M. Mortimer, B. Horan, A. Stojcevski, and S. Mekhilef, "Short-term forecasting of the output power of a building-integrated photovoltaic system using a Metaheuristic approach," *Energies*, vol. 11, no. 5, p. 1260, May 2018.
[40] M. Seyedmahmoudian, E. Jamei, G. Thirunavukkarasu, T. Soon, M. Mortimer, B. Horan, A. Stojcevski, and S. Mekhilef, "Short-term forecasting of the output power of a building-integrated photovoltaic system using a Metaheuristic approach," *Energies*, vol. 11, no. 5, p. 1260, May 2018.
[41] SSe. (2020). *SSe Prices and Tariffs*. Accessed: Nov. 25, 2021. [Online]. Available: https://products.sse.co.U.K./our-prices/view-tariffs-and-prices?Postcode=cf102gp&FuelCategory=1&TariffStatus=1
[42] BloombergNEF. (2021). *Battery Pack Prices Fall to an Average of 132/kWh, But Rising Commodity Prices Start to Bite*. Accessed: Jan. 1, 2022. [Online]. Available: https://about.bnef.com/blog/battery-pack-prices-fall-to-an-average-of-132-kwh-but-rising-commodity-prices-start-to-bite/#_ftn1
[43] Y. Zhang, Y. Xu, H. Yang, Z. Y. Dong, and R. Zhang, "Optimal whole-life-cycle planning of battery energy storage for multi-functional services in power systems," *IEEE Trans. Sustain. Energy*, vol. 11, no. 4, pp. 2077–2086, Oct. 2020.
[44] S. R. Energy. (2016). *BYD Batteries*. Accessed: Nov. 10, 2021. [Online]. Available: http://www.srenergy.co.uk/uploads/userfiles/file/BYD%20B-Box%20-%20UK.pdf

AMEENA SOROUR received the B.Eng. degree (Hons.) in electrical and electronic engineering and the M.Sc. degree in electrical energy systems from Cardiff University, Cardiff, U.K., in 2016 and 2018, respectively. She is currently pursuing the Ph.D. degree with Swansea University, Swansea, U.K. Her research interests include renewable energy and energy management systems.

MEGHDAD FAZELI (Senior Member, IEEE) received the M.Sc. and Ph.D. degrees from Nottingham University, U.K., in 2006 and 2011, respectively. From 2011 to 2012, he was a Research Assistant with Swansea University recruited on ERDF-Funded Project of Solar Photovoltaic Academic Research Consortium (SPARC), where he worked on integration of large PV systems, aimed to provide ancillary services. In 2013, he worked for couple of months on Smart Operation for Low Carbon Energy Region (SOLCER) Project as the Research Officer with Swansea University, where he became an Academic Staff with the College of Engineering, in September 2013. He is currently a Senior Lecturer with Swansea University. His research interests include integration and control of renewable energy, ancillary services, VSMs, energy management systems, and micro/nano-grids.

MOHAMMAD MONFARED (Senior Member, IEEE) received the B.Sc. degree in electrical engineering from the Ferdowsi University of Mashhad, Iran, in 2004, and the M.Sc. and Ph.D. degrees (Hons.) in electrical engineering from the Amirkabir University of Technology, Tehran, Iran, in 2006 and 2010, respectively.

In 2022, he joined the Faculty of Science and Engineering, Swansea University, U.K., and currently researches on power electronics, renewable energy systems, and energy management. He is an Associate Editor of IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS.



ASHRAF A. FAHMY received the B.Eng. degree (Hons.) in electrical engineering and the M.Sc. degree in flux vector control of electric machines from Helwan University, Cairo, Egypt, in 1992 and 1999, respectively, and the Ph.D. degree in neuro-fuzzy control of robotic manipulators from Cardiff University, U.K., in 2005. He has expertise in soft computing decision making, manufacturing systems, robotic manipulation, instrumentation, control systems, and electrical power generation. He is currently the Senior Technical Manager with the ASTUTE 2020, Engineering College, Swansea University, an Associate Professor with Helwan University (On sabbatical leave), and the Former HV Manager with the Shaker Consultancy Group. He is an Electrical Power and Machines Drive's Control Engineer by education and worldwide experience, robotics control engineer by research, and industrial manufacturing consultant by U.K. and worldwide experience.

JUSTIN R. SEARLE received the Engineering degree in analytical chemistry and the Engineering Doctorate degree in the photostability of PVC paints from Swansea University. On completion of his doctorate, he worked with Tata Colors, Shotton Works, Deeside. He is currently the Industrial Technology Director of SPECIFIC, Swansea University, U.K., leading the technical delivery teams for buildings, systems integration and technology demonstration, responsible for technology demonstration, and delivery at building scale.

RICHARD P. LEWIS received the B.Sc., M.Sc., and Ph.D. degrees from Swansea University, U.K. He is currently a Senior Technology Transfer Fellow with SPECIFIC, Swansea University.