Optimal Scheduling of a Residential Energy Prosumer Incorporating Renewable Energy Sources and Energy Storage Systems in a Day-ahead Energy Market

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Abstract

Due to the world rapid population growth, the need for energy is accelerated especially in the residential sector. One of the most efficient ways of responding to energy demand is the utilisation of energy prosumers (EPs). EPs are able to consume and produce energy by using renewable energy sources (RESs) and energy storage systems (ESSs). In this paper, optimal scheduling and operation of a residential EP is proposed considering electricity price forecasting. A hybrid adaptive network-based fuzzy inference system (ANFIS)-genetic algorithm (GA) model is proposed for day-ahead price forecasting. Then, forecasted price values are applied to a real-world EP test system. It is revealed that the proposed hybrid ANFIS-GA model can forecast electricity prices properly. However, due to the high linearity of price patterns, the proposed algorithm was not able to accurately forecast

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peak-prices. Based on the results, the optimal operation of ESSs is affected by the uncertainty of electricity price.

Keywords: Energy prosumer, day-ahead scheduling, energy storage systems, renewable energy sources, electricity price forecasting.

1 Introduction

In recent years power system has experienced radical changes to meet the growing electricity demand [1]. The most recent report of International Energy Outlook (IEO 2018) indicates a 44% growth in world demand for energy between 2018 and 2040. It also shows a 77% increase in net global electricity production during the mentioned period [2]. Nevertheless, the report additionally projects that 80% of the total produced energy in 2040 would be generated using fossil fuels. The concept of energy prosumer (EP) is one of the prominent solutions to deal with modern energy-related challenges such as zero-carbon energy production [3]. EPs are energy units able to produce energy from renewable energy sources (RESs) in addition to their traditional energy consumptions [4]. They are also equipped with energy storage systems (ESSs) so that they can enhance their economical interactions in the prosumer market. EPs typically are operated at residential level (e.g., hotels, hospital, campus, commercial location, sports centre), taking their limited capacity into consideration [5]. ESSs play a key role in optimal utilization of RESs [6]. Therefore, many of recent EPs are equipped with ESSs such as battery storage systems (BSSs) or electrical vehicles (EVs). The EPs role in the deregulated electricity market is significant. EPs have been extensively discussed by scholars [7–9] because of their collaboration in the reduction of electricity prices and their active role in the reliability increase of the power systems as well as their impacts on the desirable strategies for minimising operation costs. EPs are proactive units in smart grids (SMGs). Generally, SMGs are assumed as platforms, which permit power suppliers to adjust their strategies for bidding by considering demand-side management models. Besides, capital cost investments and system operation reliability would be amended by increasing responsiveness of the electricity suppliers.

Electricity price drew all the attention in the electricity market when the reformation of electricity was introduced into the electric power industry. Electricity price prediction is considered as critical information for electricity market participants and decision-makers. Although several methodologies have been proposed for the electricity price forecasting, which mostly differs in the model selection, data preprocessing, testing and calibration steps, the literature is limited in the field of electricity price prediction [10, 11]. The principal reason for the limited work's roots in monopoly basis of electricity supplying systems, which has resulted in limited or absence of competition in electricity markets.

Nevertheless, electricity markets are currently becoming more competitive. Therefore, electricity price prediction is acquiring its importance, and many experts are starting to take this factor into account, especially in day-ahead scheduling of EPs [12]. Indeed, energy markets are currently more open and ceaselessly providing competition, which makes electricity price prediction the centre of attention of most EPs as energy suppliers to the neighbours to invest more on introducing competent and new methods. Besides, electricity price forecasting is one of the valuable tools for most electricity participants, including EPs and traditional consumers in competitive and deregulated energy markets [13].

Different approaches have been introduced in recent works [14–17] to precisely predict the day-ahead electricity price. In this regard, the authors of [18] applied a k-factor GIGARCH process to predict electricity price in the German electricity markets. Researchers in [19] used artificial neural networks (NNs) to predict load and electricity price. Authors of [20], proposed combinatorial NN-based prediction engine to forecast the upcoming price values. In [21], an iterative NN-based forecasting technique was used for load and price forecasting. In [22], hybrid support vector machine (SVM) – genetic algorithm (GA) was utilized for price forecasting. In another study [23], SVM used for estimating the electricity price, which computes the uncertainties by forecasting the ranges of targeted quantities.

There are other researches in literature which are focused on the optimal scheduling and operation of EPs. In [24], optimal scheduling of an EP is performed in the prosumer energy market. They implemented weather forecasting based on artificial NNs to consider the RESs uncertainties in the model. However, the authors neglected to consider volatiles of electricity price in the prosumer energy market which indeed would be a considering problem. In a similar study [25], authors concentrated on the prosumer load demand forecasting by proposing a new two-level scheme for day-ahead optimal scheduling of EH. They used well-known multilayer perceptron (MLP) artificial NNs to forecast EP load demand. However, they neglected to consider price intermittency in the day-ahead electricity market. Authors in [26] analysed a hybrid EP in climate zones of Iran, where each zone has its specific electricity prices. They mentioned that different electricity prices have significant effects on the optimisation results, including net present cost and cost of energy. However, they found the utilisation of ESSs is infeasible in their optimization model. In [27], optimal scheduling of BSS has been proposed considering corrective actions on BSS in day-ahead prosumer market. Despite the effectiveness of the proposed model, authors did not propose any methodology for price forecasting. Some other researches are available that considered price forecasting in the day-ahead electricity market. In [11], optimal power dispatch strategy (OPDS) for an EP with BSS capabilities is presented. Short-term price forecasting is also applied, which is a critical decision-making tool for market players. In [28], a novel energy management system (EMS) introduced for EP which takes the uncertainty of electricity prices into consideration along with other uncertainties. The optimization problem formulated as scenario-based stochastic programming. In [29], day-ahead market price is also modeled using scenarios-based on forecast results.

By reviewing the literature, it could be observed that restricted studies are available in the field of EP scheduling, which consider price uncertainty based on the forecasting module. As also as stated in [30], comprehensive literature does not exist in the context of electricity price prediction. To fill the research gap, this paper proposed optimal scheduling of an EP by considering day-ahead electricity price forecasting. A hybrid GA-adaptive network-based fuzzy inference system (ANFIS) model is utilized to forecast electricity prices. Then, the forecasted price data is used for day-ahead scheduling of the understudy EP. The proposed method is implemented on a real-world test system in [31], and a comparison is made to investigate the impacts of electricity prices uncertainty on the EP optimization results such as ESSs optimal operation as well as operation cost of the system.

The reminder of the paper is as follows. In Section 2, methodolody of the study including hybrid GA-ANFIS model for time-series electricity price forecasting and optimization model are described. In Section 3, forecasting results and case studies are presented. Finally, the paper is concluded in Section 4.

2 Methodology

2.1 Hybrid GA-ANFIS Model for Time-Series Electricity Price Forecasting

In this study, hybrid GA-ANFIS model is used for time-series forecasting of electricity price data. Generally, in time-series forecasting, previously observed values are used for predicting upcoming values [25]. The implemented hybrid GA-ANFIS model is established upon the combination of data preprocessing, GA and ANFIS [32]. In preprocessing level, electricity values are normalised, and missing data are substituted by nought. Afterwards, ANFIS is employed to forecast future prices of electricity market while GA is applied for adjusting the membership functions in ANFIS model, which consequently would lower prediction error in short-term period. In the end, the predicted electricity prices are renormalised into the real values for performance evaluation.

ANFIS can be executed to nonlinear prediction using previously observed time-series values for training the model, which results in forecasting future values [33, 34]. The ANFIS learning ability is efficient as NNs and also benefits from the fuzzy inference system (FIS) [35, 36]. Figure 1 shows the architecture of the implemented ANFIS model in this study. The network of ANFIS is comprised of 5 layers, and each layer consists of several nodes explained by node function. During the training process, well-known GA is applied to tune the membership functions of ANFIS model parameters. In this study, triangular-shaped membership functions are considered [37]. Generally, GA is a metaheuristic computing algorithm and applications are increased in the fields of computational intelligence [35].

Flowchart of the employed hybrid GA-ANFIS model for electricity forecasting is shown in Figure 2. In the first stage, historical price data are imported from data storage centre. In the next step, data preprocessing is performed in which all price values are normalised between [0,1] according to (1). By normalizing data, training algorithm gives more precise results when all data are scaled in the same range between [0,1] [38, 39].

$$a_{norm} = b_{\min} + (b_{\max} - b_{\min}) \left(\frac{a - a_{\min}}{a_{\max} - a_{\min}} \right) \tag{1}$$

a_{norm} indicates the normalised values of price data. Also, $a_{\min}$ and $a_{\max}$ are minimum and maximum values of related parameters. The values of $b_{\min}$ and $b_{\max}$ are set as 0 and 1 respectively.

In the employed hybrid method, parameters of ANFIS membership functions are updated throughout the process of training by GA. Figure 2 shows the training process of the employed hybrid method. GA updates the randomly initialised parameters in the first step, and all parameter sets are updated step-by-step iterations until the objective function is not obtained. This study performed an offline training process to train the model using the collected data. In the prediction stage, the trained model is employed for predicting the next day's electricity prices through test data. Finally, by using

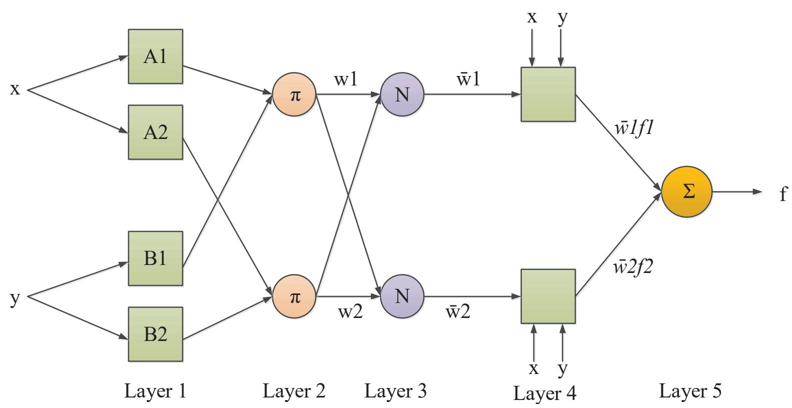


Figure 1 Architecture of a typical ANFIS model.

the inverse of the normalisation process, the forecasting results are converted back to the style of actual data in the post-processing stage. The following statical criteria in (2–4) are used for evaluating forecasting results, which are standard deviation (STD), root mean square error (RMSE), mean square error (MSE) [40–42].

$$STD = \sqrt{\sum_{p=0}^{N} \frac{(X_p - \bar{X})^2}{N-1}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{p=1}^{N}(Y_p - X_p)^2} \tag{3}$$

$$MSE = \frac{1}{N}\sum_{p=1}^{N}(Y_p - X_p)^2 \tag{4}$$

2.2 Electrical Architecture of the EP

Electrical Architecture of the understudy EP is depicted in Figure 3. The EP is equipped with clean sources of energy such as photovoltaic (PV) and wind turbine (WT) systems. The EP owns distributed energy sources (DERs), as shown in Figure 3. The electricity generated/stored is converted to dc/ac or ac/dc using the power converter unit (PCU). In this configuration, the BSS and the EV are used for acquiring market profits. These two storage units

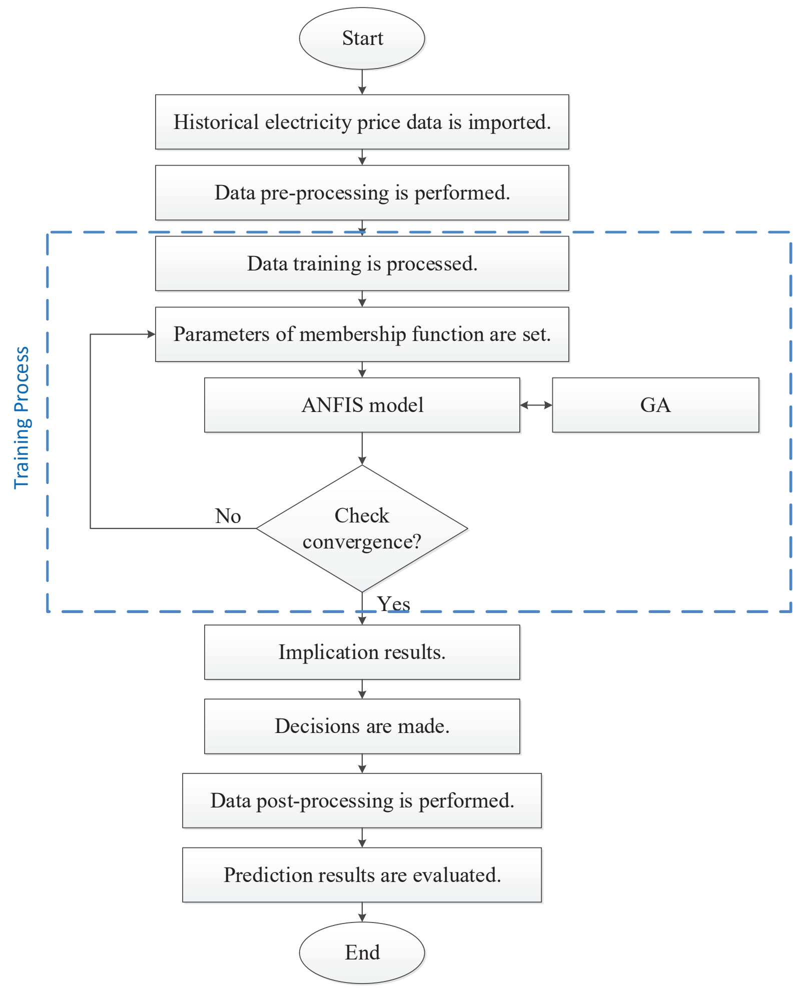


Figure 2 Flowchart of the proposed hybrid ANFIS-GA model for time-series electricity price forecasting.

are able to save electricity during lower-price periods and inject when the price of the electricity is high. In this way, they improve system economics in the day-ahead energy market. The understudy EP is committed to providing a sufficient amount of electrical power to the neighbour conventional consumers; thus, a bilateral economic trading is performed by the market players.

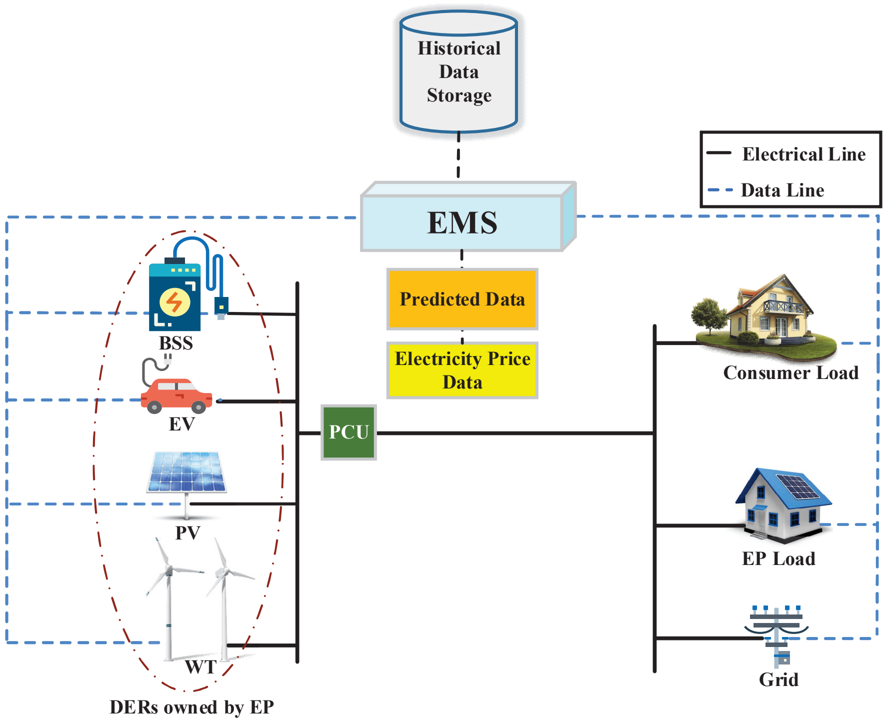


Figure 3 Understudy EP system configuration.

On the one hand, EPs are benefiting from selling electricity to neighbour consumers. On the other hand, consumers are enjoying cheaper electricity (compared to the utility prices) provided by the EP. The significance of the BSS and EV utilisation would more be highlighted in this condition. Storage units could be charged during surplus generated power as well as cheaper grid electricity prices, and discharged when the peak electricity prices arive or when energy contracts need to be fulfilled by EP.

2.3 Optimisation Problem Definition

As early mentioned, the primary purpose of the study is the optimal operation of the EP, considering the uncertainty of the electricity price. Therefore, details of the optimization problem, including objective function and optimization constraints are described in the following sub-sections.

2.3.1 Objective function

The objective function of the optimisation problem is shown in (5). The main purpose of the problem is to minimise the operation cost of the system, which is mainly electricity purchased from the grid. In the second part of the objective function depth of charge (DOD) of storage systems is minimised.

$$O.F = Min \left(\sum_{t=1}^{t_n} (P_t^E \times \tilde{K}_t) - \sum_{s=1}^{s_n} D_s^T \right) \tag{5}$$

In (5), P_t^E indicates electricity purchased/sold from/to the utility grid. $\tilde{K}_t$ shows forested electricity prices. D_s^T presents storage (BSS and EV) degradation cost, which is calculated as follows [31].

$$D_s^T = (SOC_s^{\min,EV} \times B_{EV}) + (SOC_s^{\min,BSS} \times B_{BSS}) \tag{6}$$

$$B_{BSS} = \frac{R_{BSS}}{L_{BSS} \times E_{BSS}} \tag{7}$$

$$B_{EV} = \frac{R_{EV}}{L_{EV} \times E_{EV}} \tag{8}$$

In (6), $SOC_s^{\min,EV}$ and $SOC_s^{\min,BSS}$ are minimum state of charge (SOC) of EV and BSS, respectively. Also, B_{EV} and B_{BSS} are depreciation cost coefficients per kWh for EV and BSS. R_{BSS}, L_{BSS} and E_{BSS} are respectively replacement cost (US$), lifetime (yr), and the square root of both ways of efficiency of the BSS (%). Identically, R_{EV}, L_{EV} and E_{EV} are respectively replacement cost (US$), lifetime (yr), and the square root of both ways of efficiency of the EV (%).

2.3.2 Optimization constraints

One of the essential constraints for the reliable and safe operation of EPs is the power balance equation [43], which is shown in (9). Based on this equation, energy demand by prosumer and consumer load as well as charging energy of ESSs should be equal to the energy supplied by RESs and discharging energy of ESSs. According to (10–11), exchanges power with the grid (P_t^E) is constrained to maximum and minimum values of allowable power which the EP is permitted to export or import.

$$P_t^E + P_t^{WT} + P_t^{PV} + P_t^{Discharge} = P_t^{Charge} + P_t^{Contract} + P_t^{Load} \tag{9}$$

$$P_{min}^{E} \leq P_t^E \tag{10}$$

$$P_{\max}^{E} \geq P_t^E \tag{11}$$

In (9), P_t^{WT} and P_t^{PV} are indicating the output power of WT and PV systems, respectively. WT systems convert wind speed to electrical energy and have been interested in several residential EPs in recent years. Equation (12) is used for calculating the output power of the WT unit [44].

$$P_t^{WT} = \begin{cases} 0 & v_{co} < v_t^{wind} < v_r \\ P_r \left(\dfrac{v_t^{wind} - v_{ci}}{v_r - v_{ci}} \right)^3 & v_{ci} < v_t^{wind} < v_r \\ P_r & v_r < v_t^{wind} < v_{co} \end{cases} \tag{12}$$

In (10), v_t^{wind}, v_{co}, v_{ci}, and v_r are hourly wind speed, cut-out, cut-in and rated wind speed, respectively. P_r is also the rated WT output power.

PV systems are also the other type RESs that have drawn significant attention by EPs in recent years. To calculate the output power of the PV system, Equations (13–14) are used in this study [45].

$$P_t^{PV} = A_{PV} \times G_t \times N_{PV} \times \eta_t^{PV} \tag{13}$$

In (11), A_{PV} is the area of the module (m^2), G_t refers to solar irradiance (kW/m^2), N_{PV} presents the number installed PV modules, and η_t^{PV} indicates the efficiency of PV module (%) which is calculated as (12).

$$\eta_t^{PV} = \eta_r \left[1 - \alpha \left(T_t + G_t \times \frac{NOCT - 20}{800} - T_{ref} \right) \right] \tag{14}$$

Where, η_r represents rated efficiency of PV measured at referenced temperature (25°C), α refers to the temperature coefficient for cell efficiency (0.004/°C), T_t presents hourly ambient temperature (°C), $NOCT$ is normal cell operation temperature (°C). T_{ref} shows reference temperature (25°C).

As mentioned before, ESSs play a key role in the optimal performance of the EPs. They are able to store electricity during low-price or surplus RESs power and inject in essential hours like peak-times or the hours that EP is committed to supplying power to consumers. Two types of ESSs (BSS and EV) are used in this study, which follow the same formulations as described in (15–23) [44].

$$SOC_t = SOC_{t-1} + \eta_{chargarg\ e} \times P_{chargarg\ e}(t) - \frac{P_{dischargarg\ e}(t)}{\eta_{dischargarg\ e}} \tag{15}$$

$$SOC_t \leq SOC_{max} \tag{16}$$

$$SOC_t \geq SOC_{min} \tag{17}$$

$$SOC_0 = SOC_{24} \tag{18}$$

$$P_t^{charge} \geq P_{min}^{charge} \tag{19}$$

$$P_t^{charge} \leq P_{max}^{charge} \tag{20}$$

$$P_t^{discharge} \geq P_{min}^{discharge} \tag{21}$$

$$P_t^{discharge} \leq P_{max}^{discharge} \tag{22}$$

$$U_t^{charge} + U_t^{discharge} \leq 1 \tag{23}$$

Equation (15) shows hourly ESS SOC based on charge and discharge of ESS. Equations (16–17) indicate maximum and minimum values for ESS SOC. Typically, initial and final values of ESS SOC is considered as equal, which is because of the daily operation of ESS. This constraint is shown in (18). Also, charging and discharging power of ESSs is limited to upper and lower bounds, as shown in (19–20). In this study, ESS has a binary operation. In other words, when the ESS is charging, it cannot be discharged simultaneously. Hence, Equation (23) is used for showing the binary operation of the ESS.

CPLEX solver in GAMS 24 is used for solving the mixed-integer linear programming (MILP). A private computer (PC) with 8 gig RAM and Core i5 Intel is used in this study.

3 Simulations and Results

3.1 Price Forecasting Results

Before performing price forecasting, it is essential to provide the main parameters of hybrid ANFIS-GA. Table 1 shows the provided information for hybrid ANFIS-GA parameters. Moreover, actual hourly electricity prices

Table 1 Technical parameters for ANFIS-GA model [32]

Parameter	Data
Beta	8
Alpha	0.7
Mutation	0.15
Mutation probability	0.7
Crossover probability	0.4
Population	50
Absolute training error of model for termination of program	$\leq$0.0005
Iteration	2000
Membership function	5
Epoch	50

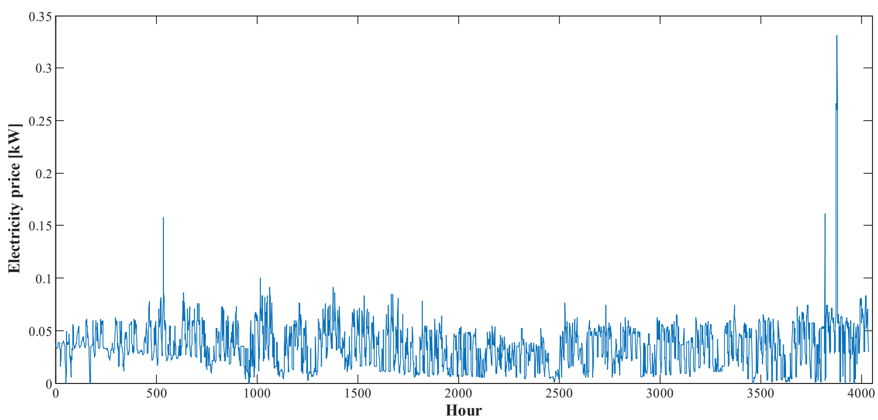


Figure 4 Hourly electricity price over 168 days.

are gathered from a local distribution company located in Iran [46]. Figure 4 shows the collected electricity price data over 168 days (January 1, 2020, to June 18, 2020). As can be seen, the intermittency of electricity price is significant, which would deviate the operation cost of the system if it is not considered. It also shows the importance of price forecasting for decision-makers and market participants.

MATLAB 2018b is used for coding the proposed hybrid ANFIS-GA model. To perform time-series electricity price forecasting, a delay of 24 hours $(t - 24)$ has been considered for forecasting the next-day electricity prices $(t + 24)$ [4]. In addition, 70% of input data has been chosen for training the model, and the other 30% of data has been reserved for testing the forecasted data [34].

Figure 5 shows electricity price forecasting results for training, testing and all data. Despite the existence of significant variations in the price data over the prediction horizon, relatively proper forecasting has been achieved by using the proposed hybrid ANFIS-GA model. Based on the results, the model was able to learn general behaviour of the patterns suitably; however, due to high nonlinearity of the price patterns, the proposed method could not predict peak prices very well. In further subsections, a comparison has been made between actual and forecasted prices in the day-ahead operation of EP. Table 2 shows statical results for the forecasted electricity price data. Regarding nonlinearity of the patterns, satisfying results have been achieved through hybrid ANFIS-GA model.

3.2 Case Studies and Results

As reviewed, some of the recent studies have been applied to short-term electricity price forecasting. However, very few of them evaluated forecasted price data in a real-world test system, especially EPs. Considering price forecasting results on a real-world test system would show the effectiveness of the forecasting in the viewpoint of system economical. Changes in operation cost of the system and possible changes in ESSs behaviour due to changes in electricity price data is a challenging task, which needs sufficient attention. Hence, case studies are introduced to evaluate the impacts of price intermittencies on the results of the optimization.

Before introducing case studies, specifications of energy equipment and other essential input data need to be described. We have tried to use the most recent studies for input data; hence, it would be possible to compare the results of this study to other available researches. Technical parameters of WT and PV are shown in Table 3. Specifications of ESS such as BSS and EV, are indicated in Table 4. Weather data, including solar irradiance, temperature, and wind speed, is extracted from [31]. The mentioned weather data is essential for calculating output power of PV and WT units. In addition, network power loss has been neglected in the proposed objective function of the study because the EP has comparatively network short-lines, which will not affect the optimization results significantly. Figure 6 shows the contracted power, which the EP is committed to fulfilling during specific hours (13:00 and 15:00) of the day. Figure 7 shows forecasted and actual electricity price

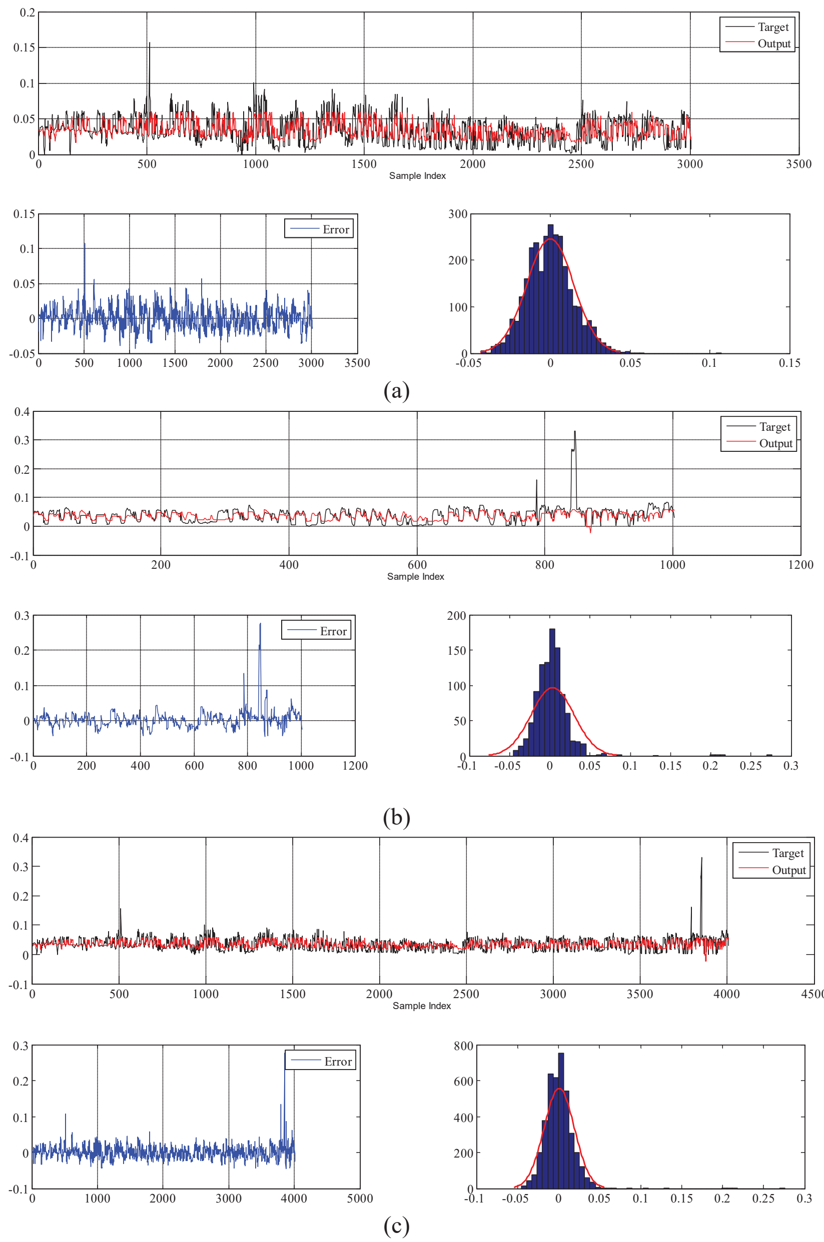


Figure 5 Electricity price forecasting results for: (a) training data; (b) testing data; (c) all data.

Table 2 Statical results for the electricity price forecasting

Statical Criteria	Train Data	Test Data	All Data
MSE	0.00021	0.00072	0.0034
RMSE	0.014686	0.026841	0.01849
STD	0.0146	0.0261	0.0184

Table 3 Specifications of PV and WT units [47]

WT Parameter	Value	PV Parameter	Value
P_{nom}	5 kW	Module Nominal Power	225 W
V_{ci}	2 m/s	α	-0.38%
V_r	12 m/s	$NOCT$	45 C
V_{co}	25 m/s	T_{ref}	25 C
		η_r	15%
		A_{PV}	1.244
		N_{PV}	30

Table 4 Technical parameters of ESSs [31]

Parameter	BSS	EV	Unit
V_n	12	12	V
SOC_0	5	4	kW
SOC_{max}	10	8	kW
P_{charge}^{min}	0	0	kW
P_{charge}^{max}	9	7	kW
$P_{discharge}^{min}$	0	0	kW
$P_{discharge}^{max}$	8	6	kW
η_{charge}	0.93	0.9	%
$\eta_{discharge}$	0.95	0.9	%
B_{BSS}, B_{EV}	0.6	0.2	US$

data for the scheduling day (a typical day in January). As mentioned before, the proposed hybrid ANFIS-GA model was able to predict the nonlinearity behaviour of the daily price pattern. To investigates the effects of price uncertainties on system optimal operation, two case studies are introduced as follows.

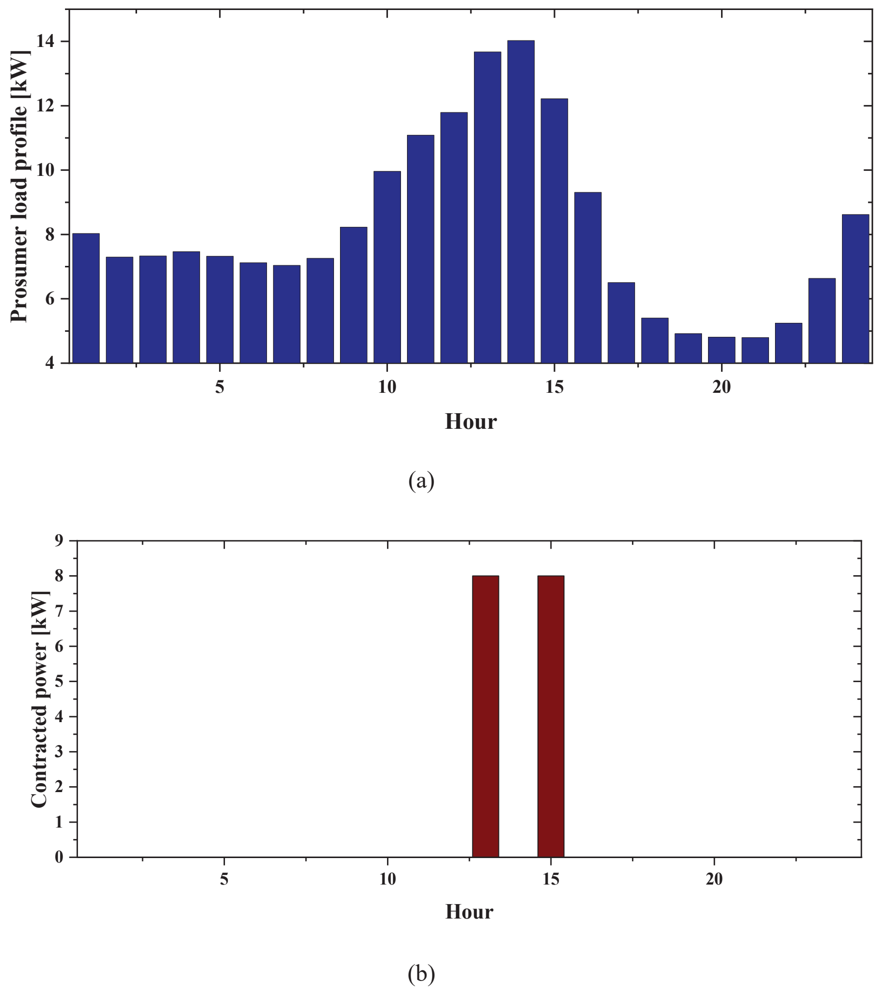


Figure 6 (a) Prosumer load profile; (b) Contracted power to neighbour consumers.

3.2.1 Case Study 1

In this case study, actual price values are used for day-ahead scheduling of a real-world EP. The operation cost of the system is achieved by 1.81142 US$. According to Figure 7, peak electricity prices occur between 17:00 and 19:00. Optimization results are shown in Figures 9–11. Figure 9 shows the exchanged power between grid and EP. As can be seen, almost a constant power rate has been imported from the grid between 1:00 to 7:00. However,

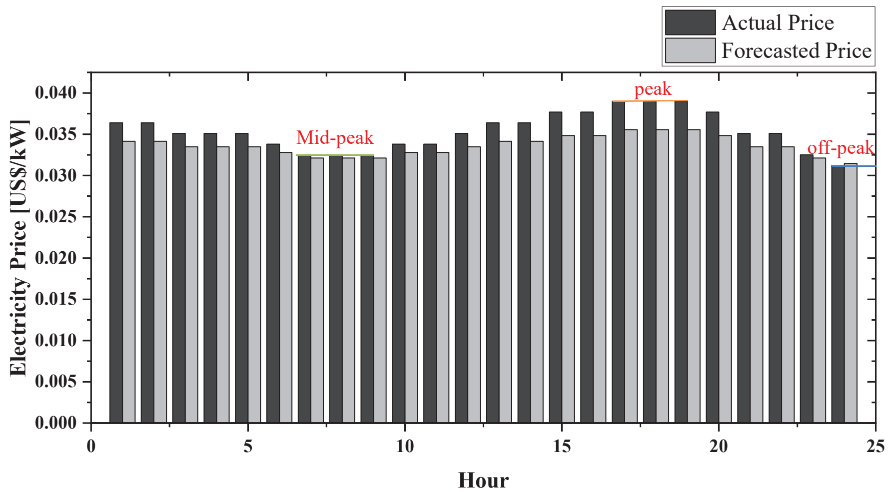
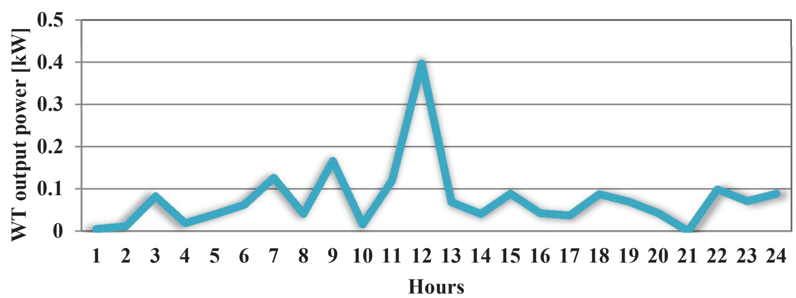
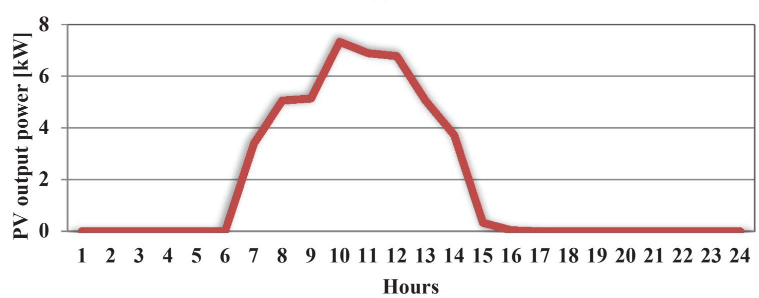


Figure 7 Forecasted and actual electricity prices for the understudy day.



(a)



(b)

Figure 8 Output power of (a) WT unit; (b) PV unit.

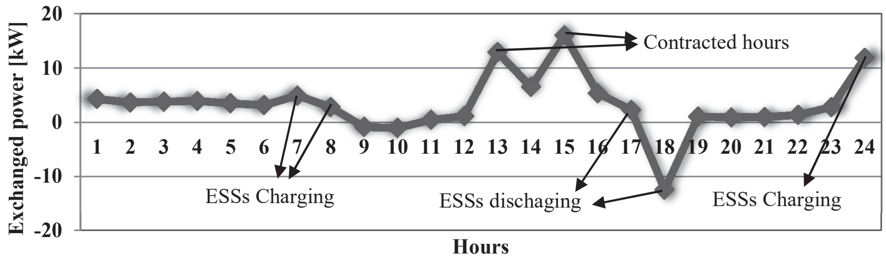


Figure 9 Prosumer exchanged power.

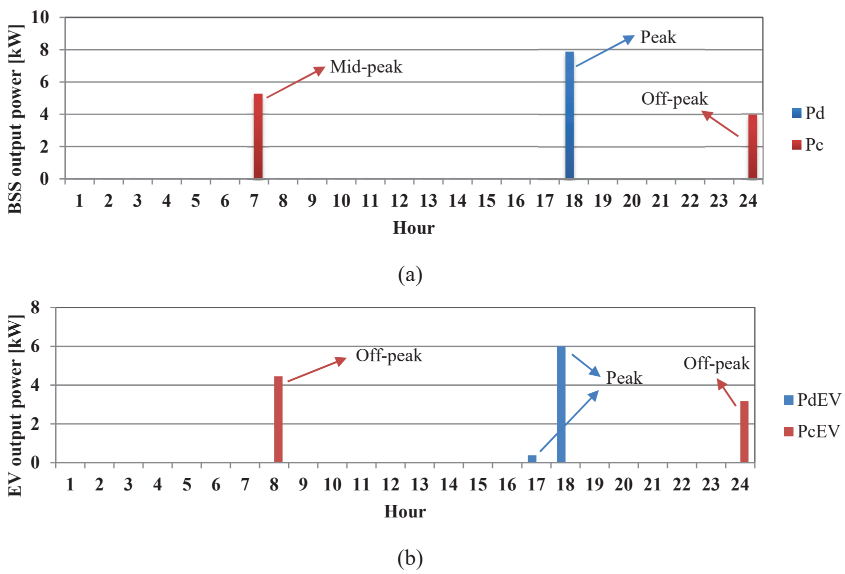


Figure 10 Charging/discharging power of (a) BSS; (b) EV during optimization.

due to the increase in RESs productions, the imported power from the grid is reduced from 8:00 to 12:00. Even it can be seen that the EP has injected power (surplus generated power of RESs) into the grid from 9:00 to 10:00. In this way, the EP is obtaining financial benefits from the bilateral interaction with the grid. Load consumption is increased between 13:00 and 15:00; hence, importing power from the grid is raised accordingly. This is because the generated power by RESs is not sufficient for supplying prosumer electrical. More importantly, the EP is committed to providing electrical power at 13:00 and 15:00 to the neighbour consumer. Therefore, a major increase can be seen in EP exchanges power at 13:00 and 15:00.

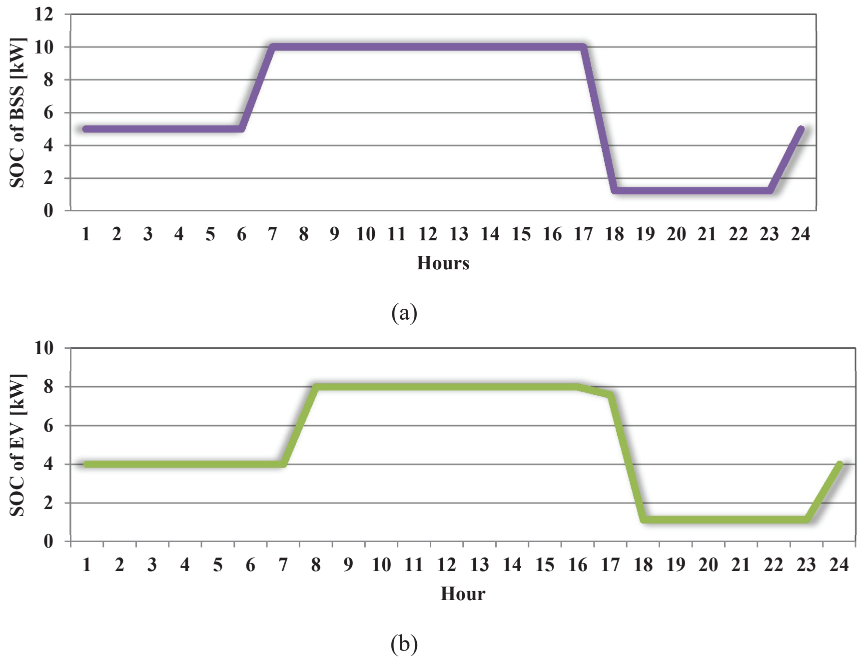


Figure 11 State of Charge (SOC) of (a) BSS; (b) EV.

Figure 10 shows the charging and discharging power of ESSs. It can be observed that both BSS and EV are charged in mid-peak and off-peak hours and also are discharged during peak hours of the day. At first, BSS and EV are charged at 7:00 and 8:00 respectively. Then, both BSS and EV are discharged at 18:00 (peak hour of the day). Also, insignificant discharge power (0.37 kW) from EV has occurred at 17:00. Figure 11 also shows the SOC of ESSs in operation day. From the results, it can be concluded that the optimal operation of both BSS and EV highly depends on electricity price values. In other words, ESSs react to electricity price changes. Hence, Therefore, it is essential to pay attention to changes in electricity prices in day-ahead EP scheduling.

3.2.2 Case Study 2

In this case, predicted values of electricity price are used for day-ahead optimization of the EP. The operation cost of the system is achieved at 2.645 US$. Overall values of forecasted price are less than actual values, especially at peak hours. By investigating hourly electricity price values, it

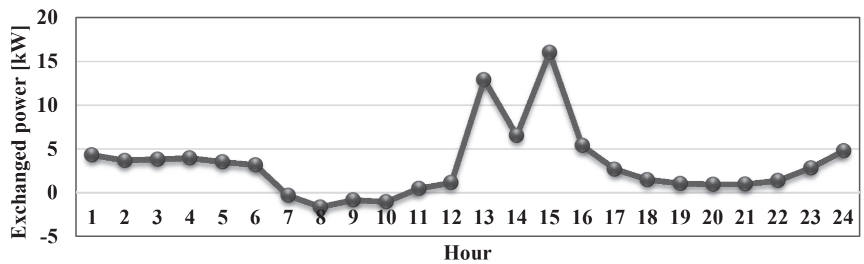
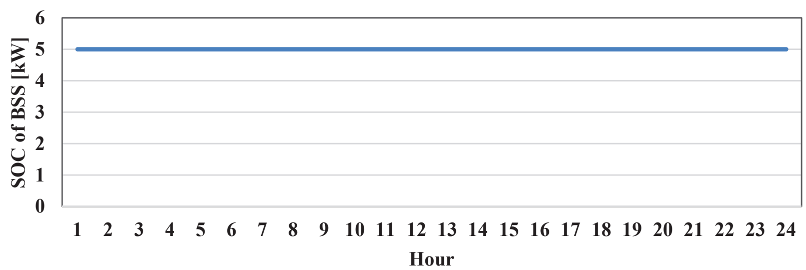
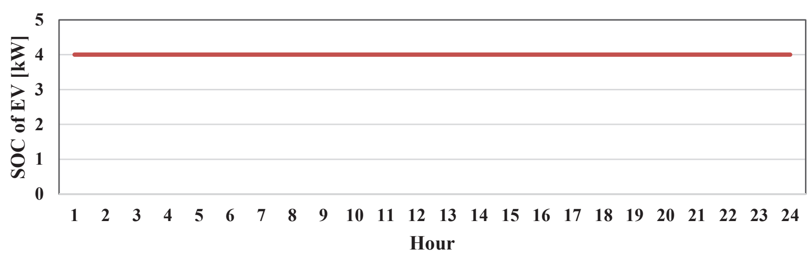


Figure 12 Prosumer exchanged power.



(a)



(b)

Figure 13 State of Charge (SOC) of (a) BSS; (b) EV.

can be observed that the proposed hybrid-GA model could not predict peak prices accurately. Therefore, the difference between peak prices and off-peak prices are not significant compared to actual price data. In other words, the nonlinearity of price pattern is decreased in this condition.

Figure 12 shows the EP exchanged power in operation day. The general behaviour of the system is similar to the previous case study. However, due to lower electricity prices, it was not economical to utilise ESSs in the day-ahead operation of EP (Figure 13). Based on the results, it is concluded that

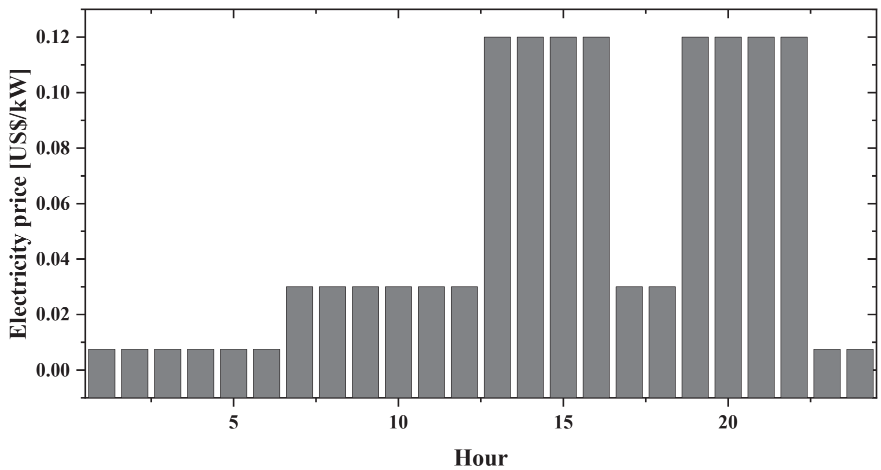


Figure 14 Extracted electricity price data from [31].

the utilisation of ESSs is highly dependent on hourly electricity prices. In cases with higher electricity prices, more interactions of ESSs are expected while lower electricity prices result in less interaction of ESSs in the daily operation of EP. It is noteworthy that ESSs, in addition to their economic benefits, also play a constructive role in peak-shaving purposes, especially when the difference between peak and off-peak prices is remarkable.

To validate optimization results, a comparison has been made with the previous study [31]. The extracted electricity price data is illustrated in Figure 14. As can be seen, the difference between off-peak and peak prices is significant, which consequently would affect the operation of ESSs in the day-ahead electricity market. As a result, more charge/discharge from ESSs is expected under this condition (Figure 15). The operation cost of the system is also raised in this condition. The total operation cost of the system is achieved as 20.353 US$. Due to higher electricity price values, such an increase in operation cost of the system is obtained. It is noteworthy that the applied electricity price data is based on the constant rates over the operational day. However, optimal operation of EPs under uncertainty of electricity price is a challenging problem that depends on various factors such as accuracy of price forecasting. In this paper, we tried to emphasise the importance of electricity price forecasting on the optimal operation of the EPs. It was shown that by the changes in the electricity price values, optimisation results would face meaningful changes. Also, it was revealed that the operation cost of the

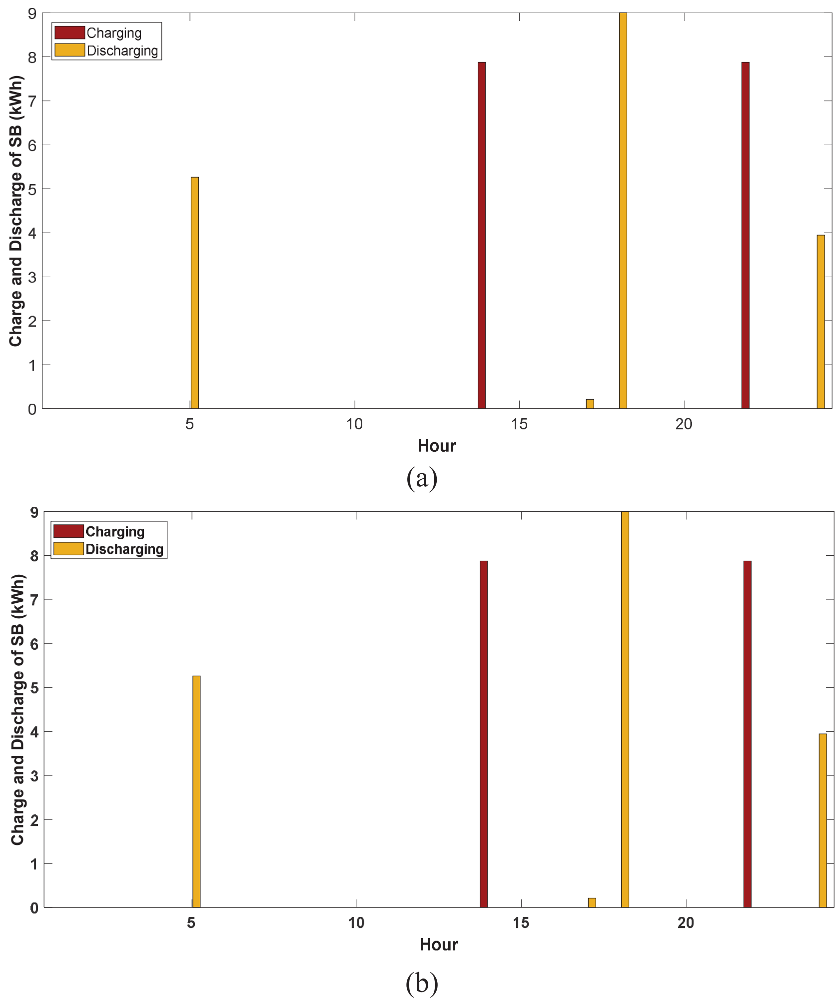


Figure 15 Charging and discharging of: (a) BSS; and (b) EV.

system, as well as ESSs optimal operation, are highly dependent on electricity price values.

4 Conclusions

This paper proposed optimal scheduling and operation of EP by considering electricity price forecasting. A hybrid ANFIS-GA model implemented for day-ahead electricity price prediction. According to forecasting results, the suggested hybrid model was able to predict nonlinear electricity price patterns in a proper way. The values of MSE, RMSE and STD achieved as 0.0034, 0.01849, and 0.0184 respectively. However, the proposed algorithm could not predict peak prices accurately. Two case studies were introduced to evaluate the effects of load uncertainty on the optimal operation of the EP test system. It was revealed that electricity price has a considerable effect on the optimal operation of EP, especially on the operation of ESSs. Under the actual electricity prices, ESSs incorporated in optimal energy trading of the EP. However, particularly in this research, ESSs did not participate in the optimal operation of EP by using forecasted electricity price data. Since the algorithm was not able to forecast peak prices accurately, general forecasted price values are less compared to actual values, especially in peak hours.

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