Sustainable Energy Technologies and Assessments 39 (2020) 100722

Contents lists available at ScienceDirect

Sustainable Energy Technologies and Assessments

journal homepage: www.elsevier.com/locate/seta

Original article

Two-stage stochastic home energy management strategy considering electric vehicle and battery energy storage system: An ANN-based scenario generation methodology

Saeed Zeynali[a], Naghi Rostami[a,*], Ali Ahmadian[b], Ali Elkamel[c,d]

[a] Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran
[b] Department of Electrical Engineering, University of Bonab, Bonab, Iran
[c] Department of Chemical Engineering and Department of Systems Engineering, University of Waterloo, Waterloo, Canada
[d] Department of Chemical Engineering & Gas Research Center (GRC), Khalifa University of Science and Technology, Abu Dhabi, United Arab Emirates

ARTICLE INFO

Keywords:
Home energy management system
Stochastic programming
ANN-based forecasting
Battery degradation cost model
Electric vehicle
Battery energy storage system

ABSTRACT

This study implements two-stage stochastic programming in a smart home application to reduce the electricity procurement cost of an ordinary household. In this concern, vehicle to home (V2H) capability of the available electric vehicle (EV) is used in coordination with battery energy storage system (BESS) under control of a home energy management system. The stochastic decision variables are the charge-discharge power of these components. The uncertainties derived from the power production of the roof-mounted solar photovoltaic panels, household's load demand, real-time electricity price are assimilated into the problem. Besides, to create the stochastic process, an artificial neural network (ANN) is trained using historical time series. Furthermore, as one of the main contributions, a proper analytical battery degradation cost model is integrated into the problem. Hence, different schemes such as with and without degradation cost, with and without BESS and uncoordinated charging are investigated under various charging rates. Also, the sensitivity of the problem for different charging rates of the EV and BESS is analyzed. Furthermore, the influence of probable future battery storage cost reductions on the home energy management system is investigated. Eventually, the efficiency of the stochastic programming method is analyzed by the value of stochastic solution (VSS) metric.

Introduction

Transportation electrification is a promising paradigm in confrontation with the well-known environmental issues rooting from conventional fossil fuels [1,2]. Therefore, a notably large amount of augmentation is expected in penetration level of electric vehicles (EVs) [3], which opens the doors for new opportunities. For instance, from the early emergence of modern EVs, the idea of using their battery as a supporting storage unit has been relatively popular among the researchers [4]. The main concept is to control charge–discharge patterns of an idle EV, to achieve various objectives, such as lower cost, enhanced voltage profile, or flattened peak load [5,6]. On the one hand, some researchers propose the coordinated scheduling of these vehicles under an aggregator for providing an ancillary vehicle to grid (V2G) service [7]. On the other hand, some researchers simply propose vehicle to home (V2H) mode, wherein the vehicle provides service only for the proprietor under the control of the home energy management system (HEMS) [8]. It should be noted that the HEMS can manage the operation of numerous devices, such as battery energy storage system (BESS), household appliances, or thermotical loads to achieve the desired objectives.

In this regard, some noteworthy contributions have been made by [9–14]. Reference [9] have investigated different charging strategies to reduce household electricity consumption price by using only the EV's battery. The optimal BESS sizing for HEMS has been investigated via [10]. Nevertheless, the presence of EV is ignored in the problem. In [11], a load-leveling algorithm is proposed for coordinated scheduling of demand response capabilities of residential appliances and charging patterns of EV. Alirezaei et al. [12] have investigated the design of a zero-energy building by integrating solar energy and V2H capability to serve as an energy storage system. Similarly, reference [13] represents the results of a real-world project, aiming to achieve a zero-energy green village through fuel cell electric vehicle to grid and photovoltaic (PV) solar panels. The authors have made a proper economic viability analysis and proved that the energy dependency could be reduced up to 71%. In [14], optimal operation and sizing of the BESS is minutely

* Corresponding author.
E-mail address: n-rostami@tabrizu.ac.ir (N. Rostami).

https://doi.org/10.1016/j.seta.2020.100722
Received 17 February 2020; Received in revised form 11 April 2020; Accepted 4 May 2020

Nomenclature

Q	General form of a stochastic objective function
x	Vector of here and now decision variables
ω	Stochastic process
G	Vector of wait and see decision variables
N	Stochastic process in standard normal space
Z	Objective variable
NS	Number of stochastic scenarios
π	Probability
T	Duration of the scheduling (Hours)
λ	Electricity price ($/kWh)
L	Load demand of the household (kW)
sp	Solar power generation of PV panels (kW)
ch	Binary variable which is 1 for charging periods
pch	Charging power (kW)
dch	Binary variable which is 1 for discharging periods
$pdch$	Discharging power (kW)
Deg	Battery degradation cost ($)
η^{pv}	Efficiency of the solar PV panels
S^{pv}	Area of the solar PV panels (m^2)
ϕ	Solar irradiation power (kW/m^2)
T^{pv}	Ambient temperature of the solar PV panels (°C)
SOC	State of charge
η^{ch}	Charging efficiency
η^{dch}	Discharging efficiency
Cr	Maximum allowable charging rate (kW)
$SOC^{\min}$	Minimum allowable SOC value
$SOC^{\max}$	Maximum allowable SOC value
$P_{\inf}$	Power limitation of the infrastructure (kW)
δ	Cycle depth
E	Battery storage capacity
Ψ	Cycle depth aging function
C	Marginal degradation cost ($/kW)
R	Battery storage cost ($)
VSS	Value of stochastic solution
Z^D	Objective function in deterministic case
Z^S	Objective function in stochastic case
Φ	Standard normal cumulative distribution function
EF_Y	Empirical cumulative distribution function of the original stochastic process
Y_{ANN}	Stochastic process obtained from ANN-based scenario generation
Y_{org}	Stochastic process in original distribution space

Indices

s	Scenario index
t	Time index
k	Storage type index (EV or BESS)

Acronyms

EV	Electric vehicle
PEV	Plug-in electric vehicle
BESS	Battery energy storage
HEMS	Home energy management system
ANN	Artificial neural network
PV	Photovoltaic
V2H	Vehicle to home
PDF	probability distribution function
WD	With degradation cost
SC	Scheme
GAMS	General algebraic modelling system
MINLP	Mixed-integer nonlinear programming

inspected in the presence of PEVs and PV arrays. The authors have considered different operation modes, different BESS technologies, and prices.

The problem, however, is that none of the aforementioned studies have addressed the inherent uncertainties of renewable energy sources which will most definitely affect the optimal operation and scheduling. Moreover, none of them have considered the battery degradation cost. In view of the uncertain nature of the problem, different uncertainty-handling methodologies have been explored by [15–20]. In [15] a stochastic optimization framework has been proposed for HEMS, which considers three different operation schemes on a typical day using PEV as an energy storage unit. Reference [16] has proposed a joint optimization model for simultaneous scheduling of thermostatically controlled appliances and charging scheduling of EV in a small-scale residential site. The authors have integrated a model predictive control strategy to handle estimation errors. A stochastic HEMS is proposed in [17], wherein Markov-chain of PEVs mobility is obtained. Nonetheless, home power demand and PV power generation assumed to be perfectly forecasted. Reference [18] investigates the cooperation of wind turbine, demand response program and fuel cell vehicle under control of HEMS. A Monte-Carlo simulation-based meta-heuristics optimization algorithm is proposed, which only accounts for the uncertainties of wind energy production. Evidently, it is a computationally burdensome method for a scheduling problem. A multi-stage linear stochastic programming approach is adopted by reference [19] to handle the uncertainties of household's load demand in optimal operation scheduling of a PEV. The proposed linear problem aims to reduce the cost of electricity procurement within the time of use pricing environment. In [20], bidirectional energy flow between the EV and power grid is examined under deterministic and stochastic case scenarios.

BESS or EVs battery storage are expensive components which undergo a notable amount of degradation while providing ancillary services [21,22]. For this reason, it is quite essential to integrate a proper battery degradation cost model into the problem which is disregarded in all the above-mentioned literature. Almost all of the aforementioned research on the subject have either ignored some uncertainties or they have not used a proper scenario generation and forecasting methodology, which can handle the interdependency and autocorrelation of the random variables [23]. They have mainly used random sampling methods such as Monte-Carlo simulation.

In the field of degradation cost, Ahmadian et al. [24] have made some remarkable contributions to the literature. The authors have proposed some simple polynomial and exponential functions which account for different aspects of degradation modeling, such as power rating degradation, depth of discharge degradation, and calendar degradation. That is to say, this method requires a suitable cycle-counting algorithm such as rain-flow method [25], which makes the problem inapplicable to modern optimization software since they require an appropriate mathematical expression. The problem can only be solved by a powerful meta-heuristic algorithm which imposes unreasonably high computational burden for an operation scheduling problem. On account of these drawbacks, authors in [26] have propose a simplified degradation cost model based on life-cycle degradation function. Furthermore, the authors have applied this methodology into optimal operation problem of a large-scale BESS. The method is proven to be nearly as accurate as the rain-flow method.

To address the pros and cons of the current literature in the field of HEMS, and integrate a proper uncertainty handling methodology, this paper proposes a two-stage stochastic [27] optimal HEMS scheduling methodology, which simultaneously schedules an EV and a BESS, which is particularly necessary, on account of availability limitations of EVs. The uncertainties of real-time electricity price, household's load demand, and power generation of solar PV panels are considered. The linear regression models [28–30] have been widely used in the literature for prediction and stochastic process generation. However, they fail to interpret non-linear interdependencies between the time series lags [31–34]. For this reason, in this study, an artificial neural network (ANN) scenario generation method is adopted from [35], which not only captures the non-linear and linear interdependencies, but also provides a reliable set of stochastic scenarios. Additionally, the degradation cost model proposed by [26] is integrated into the problem which makes the model more realistic. Different scheduling schemes, such as with BESS, without BESS and uncoordinated charging modes, are thoroughly inspected in the presence and absence of battery degradation cost. Eventually, the value of stochastic solution (VSS) is calculated to prove the efficiency of the stochastic programming method in comparison the previous deterministic studies. The overall structure of the proposed HEMS scheduling is illustrated by Fig. 1. The obtained results in this study are quite different from the delusional results of the studies which have ignored battery degradation cost, since in the long term, degradation cost dominates the obtained profit by a considerably large margin. It is observed that the uncoordinated charging imposes the highest cost on the household electricity bill. The coordinated scheduling of BESS and EV is the most cost-efficient scheme. Additionally, this study conducts battery cost-sensitivity analysis, which shows that the coordinated scheduling of EV and BESS has the highest sensitivity for possible battery cost reductions in future, while when the EV is scheduled individually, it is less sensitive for the battery cost decrement. Likewise, the maximum power rate-sensitivity analysis proves that increasing EV's maximum charging rate is way more effective on the cost reduction in comparison with BESS's charging rate.

The leading contributions of this study can be summarized as follows:

- The uncertainties of free electricity market price, solar irradiation, and households load demand is handled by two-stage stochastic programming
- An analytical battery degradation cost is included in HEMS scheduling.
- An ANN-based scenario generation is used for autocorrelated random variables.
- A battery cost-sensitivity analysis is conducted on the HEMS scheduling.
- The effect of different maximum charging rates is considered in the problem.

The paper is organized as follows: The problem statement is introduced in Section 2. Section 3 elaborates the proposed ANN-based forecasting and scenario generation. The results are demonstrated in Section 4. Finally, Section 5 draws the conclusions and speculations on possible future studies.

Problem statement

Stochastic programming

Almost all of the real-world problems have some uncertain parameters. Conventionally, these uncertainties were handled by approximating them with expected or forecasted values [36], which clearly fails to provide robust results even with the best forecasting tools [37]. Therefore, the stochastic programming approach has been proposed [38], which can take all the possible realizations of the uncertain parameters into account, and provide a solution which is relatively optimal. Due to the computational limitations of the current processing units, the number of possible outcomes is compressed in finite number of scenarios. Two-stage stochastic programming is the most commonly used stochastic decision-making method [39]. The first stage decision variables are determined for deterministic parameters which are referred as here-and-now decision variable, and they are independent from the outcomes of the stochastic process. The second-stage decision variable, however, are defined separately for every single scenario. Consequently, they depend on the realization of the stochastic process, and they are denoted as wait-and-see variables. The objective of stochastic program is to minimize or maximize the expected value of fitness function while satisfying the necessary constraints in every single scenario. The overall structure of two-stage stochastic programming is defined as follows:

$$\min. \sum_{s=1}^{NS} \pi_s Q(x, \omega_s, G_s) \tag{1}$$

$$\pi_s = p(s|\omega = \omega_s) \ , \ \sum_{s=1}^{NS} \pi_s = 1 \tag{2}$$

Stochastic programming has been successfully applied to a wide range of problems considering power system studies and energy management problems [27,40]. More information about stochastic programming can be found in [41].

Problem formulation

The objective of the two-stage stochastic energy management problem is to reduce electricity consumption cost of a household through smart coordination of V2H and BESS. To put it in another way, the stochastic decision variables are charge-discharge power of the available personal EV and the BESS. The scenario variable stochastic problem is formulated as follows:

$$\begin{aligned} \min Z &= \sum_{s=1}^{NS} \pi_s \sum_{t=t_0}^{t=T} \lambda_{s,t} \times \Bigg(L_{s,t} - sp_{s,t} + \sum_k ch_{s,t,k} \times pch_{s,t,k} \\ &\quad - dch_{s,t,k} \times pdch_{s,t,k} \Bigg) + \sum_k Deg_{s,t,k} \end{aligned} \tag{3}$$

$$\begin{aligned} sp_{s,t} &= \eta^{pv} S^{pv} \phi_{s,t} (1 - 0.005(T^{pv} - 25)) \\ &\quad s = 1, 2, \ldots, NS \quad t = 1, 2, \ldots T \end{aligned} \tag{4}$$

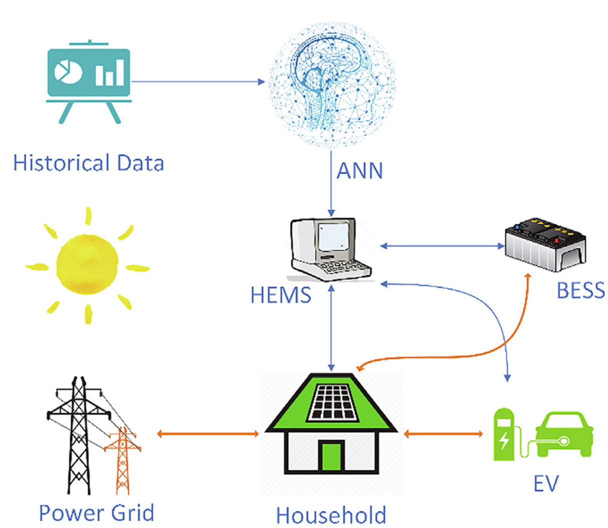

Fig. 1. The overall schematic of the proposed HEMS scheduling: red lined demonstrate the power flow while the blue lines are for information flow.

$$SOC_{s,t,k} = SOC_{s,t-1,k} + ch_{s,t,k} \times pch_{s,t,k} \times \eta_k^{ch} - dch_{s,t,k} \times pdch_{s,t,k}/\eta_k^{dch} \quad s = 1, 2, ..., NS \quad t = 1, 2, ...T \quad k = EV, ES \tag{5}$$

$$0 \leqslant pch_{s,t,k} \leqslant Cr_k \quad 0 \leqslant pdch_{s,t,k} \leqslant Cr_k \quad s = 1, 2, ..., NS \quad t = 1, 2, ...T \quad k = EV, ES \tag{6}$$

$$SOC_k^{\min} \leqslant SOC_{s,t,k} \leqslant SOC_k^{\max} \quad s = 1, 2, ..., NS \quad t = 1, 2, ..., T \quad k = EV, ES \tag{7}$$

$$-p_{\inf} \leqslant L_{s,t} - sp_{s,t} + \sum_k ch_{s,t,k} \times pch_{s,t,k} - dch_{s,t,k} \times pdch_{s,t,k} \leqslant p_{\inf} \quad s = 1, 2, ..., NS \quad t = 1, 2, ..., T \tag{8}$$

$$ch_{s,t,k} + dch_{s,t,k} = 1 \quad s = 1, 2, ..., NS \quad t = 1, 2, ..., T \quad k = EV, ES \tag{9}$$

$$pch_{s,t,k} - pch_{s-1,t,k} = 0 \quad pdch_{s,t,k} - pdch_{s-1,t,k} = 0 \quad ch_{s,t,k} - ch_{s-1,t,k} = 0 \quad dch_{s,t,k} - dch_{s-1,t,k} = 0 \quad s = 1, 2, .., NS \quad t = t_0 \quad k = EV, ES \tag{10}$$

The objective function is declared in (3), which minimizes the mean value of cost over the stochastic process. The first term of the objective function is the mean value of the electricity provision cost, while the second term represents the mean value of battery degradation cost of EV and BESS. The corresponding solar power generation in every hour of each scenario is calculated via (4). State of charge in every time step for EV and BESS is calculated via (5) [42]. Equation (6) defines the upper and lower bounds of charge-discharge variables. Equation (7) prevents overcharge and deep discharge states [43]. The power limit of the residential infrastructure is declared by (8). Evidently, EV or BESS cannot charge and discharge simultaneously; this condition is ensured by the binary equality in (9). The non-anticaptivity constraints are stated in (10), which denotes scenario-independency of the first-stage stochastic variables. The battery degradation cost term is expressed as follows:

$$\delta_{s,t,k} = \frac{pdch_{s,t,k}}{\eta^{dch} E_k} + \delta_{s,t-1,k} \qquad s = 1, 2, ..., NS \quad t = 1, 2, ..., T \quad k = EV, ES \tag{11}$$

$$\Psi(\delta_{s,t,k}) = 5.24e - 4(\delta_{s,t,k})^{2.03} \tag{12}$$

$$C_{s,t,k} = R_k \times \frac{\partial\Psi(\delta_{s,t,k})}{\partial pdch_{s,t,k}} = R_k \times \frac{\partial\Psi(\delta_{s,t,k})}{\partial\delta_{s,t,k}} \times \frac{\partial\delta_{s,t,k}}{\partial pdch_{s,t,k}} = 10.63e - 4 \times \frac{R_k}{\eta^{dch} E_k} \times \delta_{s,t,k}^{1.03} \quad s = 1, 2, ..., NS \quad t = 1, 2, ..., T \quad k = EV, ES \tag{13}$$

$$Deg_{s,t,k} = pdch_{s,t,k} \times C_{s,t,k} \qquad s = 1, 2, ..., NS \quad t = 1, 2, ..., T \quad k = EV, ES \tag{14}$$

The cycle depth is defined by (11), wherein the *pdch* is a positive variable. The cycle life aging function is denoted by (12), which is an approximately quadratic function. The marginal electricity cost is established in (13), which is adopted from [26,44]. Eventually, the degradation cost at every hour for every scenario and for either EV or BESS is defined by (14).

Optimization method

As it was stated earlier, the number of scenarios in the stochastic problem, defines its computational burden. The higher the number of scenarios get, the more the accuracy and computational burden will be. Therefore, stochastic problems consist of numerous decision variables, which necessitates the usage of a powerful and speedy optimization method, and it is particularly essential for a short-term scheduling problem [45]. Nevertheless, implementing such a complicated algorithm might be difficult for a power system researcher. In this regard, the commercially available general algebraic modeling system (GAMS) software is an effective and easy-to-use tool [46]. The main advantage of GAMS is combining novel mathematical method with traditional computer codding, which can solve a wide range of linear and nonlinear problems, and it is especially effective for solving stochastic problems since they can be solved by decomposition methods [47]. GAMS has been proven to be efficient in a wide range of engineering and power system problems [48–50]. In this study, the problem is solved by KNITRO solver, which is designed for large-scale mixed integer non-linear problems (MINLPs), and it deploys novel interior-point and active set methods [51]. The algorithm also uses trust regions to accelerate the convergence. KNITRO can solve system of nonlinear equation, large-scale constrained, and unconstrained mixed integer nonlinear and linear problems [52]. These characteristics make it an ideal solver for the current study.

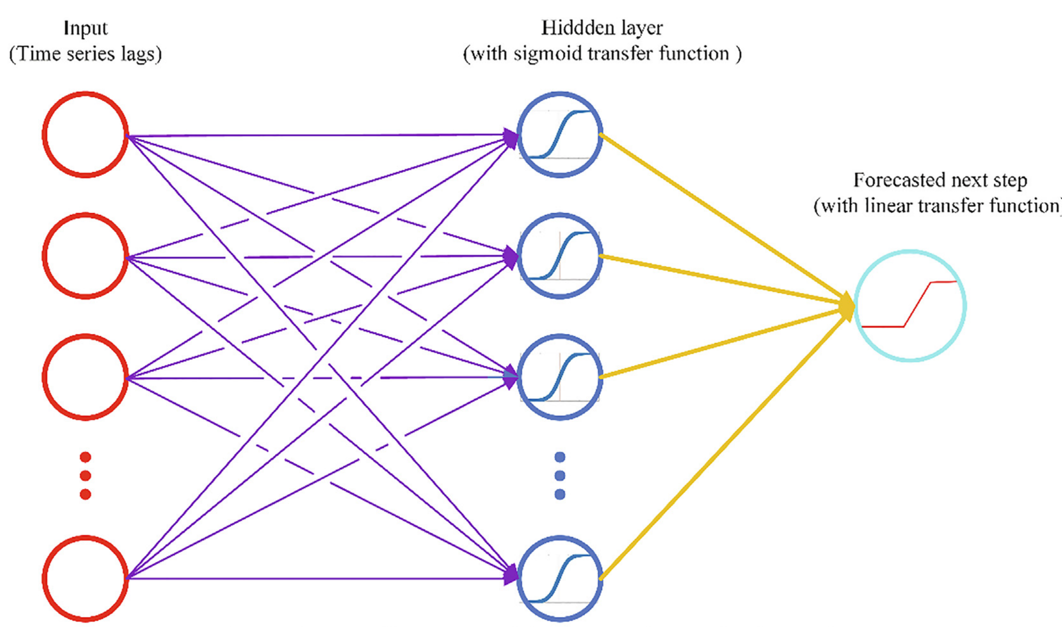

Fig. 2. The overall structure of the proposed ANN for forecasting.

ANN-based forecasting

Artificial neural networks (ANNs) are non-linear and nonparametric data-fitting methods, which can capture non-linear dependencies between parameters far better than the conventional linear models [53]. For a set of input and output data, the corresponding tuning parameters (weights) of ANN should be set appropriately, which is referred to as training methods [54]. In this case, the inputs are historical time-series lags, and the single output is the one step ahead forecasted value. In this study, a three-layer (one input layer, one output layer, and one hidden layer) feed-forward ANN is used, and the weight parameters are calculated by scaled conjugate gradient backpropagation algorithm in an iterative procedure [55]. For the sake of preventing the overfitting over the data [56], a percentage of data is reserved for validation. If the value of error does not decrease for validation data in a predefined number of consecutive iterations, the termination criterion will be satisfied, and the training will stop. Eventually, the sigmoid transfer function is used in hidden layer neurons, and the linear transfer function is used in output-neuron. The overall structure of the proposed ANN is demonstrated by Fig. 2.

The number of neurons and layers are selected based on trial and error and suggestions in the literature [57]. Furthermore, the time series lags with the highest autocorrelation are chosen as input since they have the most effect on the output. In the next step, the time series of prediction error for the proposed ANN is calculated as the difference between estimated and testing values which are a percentage of main data that aren't used in training phase, and they ensure that ANN is trained properly. The result shows that the error time series consists of very low autocorrelation value with almost zero mean. Hence, it is considered as white noise with normal probability distribution function (PDF) of N(0, σ) [47], with zero mean and standard deviation of σ. In an iterative procedure, the aforementioned white noise is added to the previously predicted values to create different scenario paths for the stochastic programming. This process is continued until the desired number of scenarios is generated [35]. Since the error term follows a normal PDF, it is quite appropriate for residential loads and electricity price [58]. However, solar irradiation does not follow any specific PDF. In other words, at any hour, a different distribution might be compatible with historical data [59]. In this study, first the solar irradiation scenarios are created assuming that they follow normal PDF, then using fairly large amount of historical data the empirical cumulative distribution function of solar irradiation is obtained and by using inverse transformation method the scenarios are transformed from normal PDF to this empirical PDF space as it is demonstrated by (15)-(16). In this way, the original distribution of data will be preserved while using the capability of ANN-based forecasting. More information about inverse transformation can be found in [60]. The flowchart diagram of the proposed stochastic scenario generation method is illustrated by Fig. 3.

$$N = \Phi^{-1}[EF_Y(Y_{ANN})] \tag{15}$$

$$Y_{org} = EF_Y^{-1}[\Phi(N)] \tag{16}$$

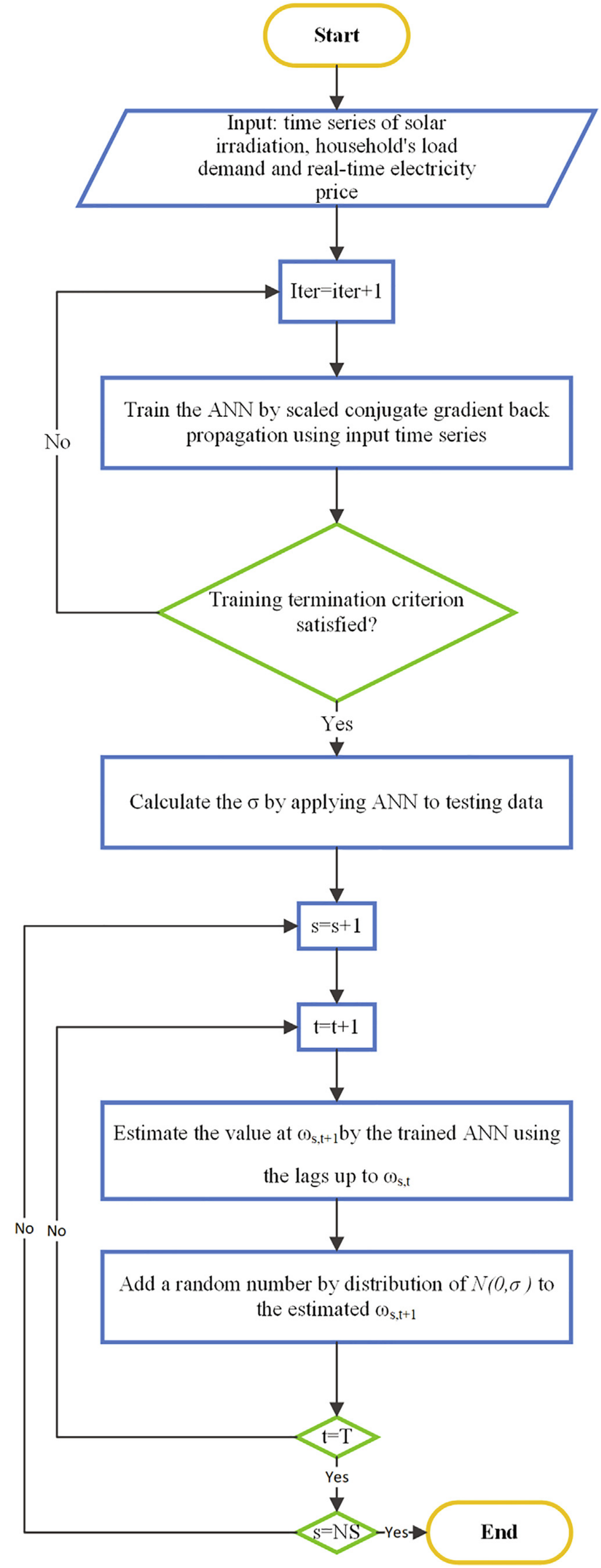

Fig. 3. The flowchart diagram of the proposed scenario generation algorithm.

Simulation results and discussion

The proposed two-stage stochastic programming methodology is applied to HEMS operation scheduling of a case study household which is assumed to have an available EV, BESS, and solar PV arrays. The related data is obtained from [38,45]. The results of different operation modes are summarized in this section. Table 1 represents the main characteristics of the understudy home, EV, BESS, and PV panels. The parameters of the first-stage (here and now) are considered to be SOC of the vehicle at arrival time, solar irradiation, electricity price, and household's load demand. Since real-time electricity market is cleared every five minutes [61] this is a proper assumption. The arrival time is considered to be a known parameter and it is the first stage of the

Table 1
Parameters of the understudy system.

Household and PV panel parameters	value
Solar PV capacity(kWh)	8
Efficiency of solar PV	0.13
Peak load of home(kWh)	4
Power limit of the infrastructure (kW)	20
EV parameters	value
Arrival time or EV (first stage) (hour)	17
Departure time (hour)	6
Battery capacity (kWh)	50
Battery replacement cost ($)	11,000
Charging/discharge rate (kW)	5,7,10
Initial SOC	0.4
Final SOC	0.9
Minimum and maximum SOC level	0.2, 1
BESS parameters	value
Capacity	40
Replacement cost	9000
Charge/discharge rate	15
Initial SOC	0.4
Final SOC	0.4
Minimum and maximum SOC level	0.2,1

stochastic program. In other words, the operation scheduling starts at the arrival time of the vehicle. Whereas, the departure time is assumed to be user-defined. The proposed ANN with 30 neurons in the hidden layer is trained by using 10 lags of the historical time series data. Afterward, the scenario generation algorithm is applied to create stochastic scenarios. Fig. 4 demonstrates a segment of the training, validation and testing error time series of the proposed ANN in estimating solar irradiation. This figure illustrates the real value of the historical data, the value estimated by the ANN, and the error value, which is the difference between real and estimated values. The generated scenarios, estimated values and forecasted values for electricity price, solar irradiation and residential load demand are illustrated by Fig. 5. As can be seen, the mean value of the error term is almost zero and the overall variations are very small. However, in some irregular scenarios, unexpectedly high estimation errors are inevitable in every forecasting algorithm. Besides, unlike point forecast methods [36] a majority of stochastic scenarios are included in the problem which reflects real-world conditions. To get a better understanding of the proposed methodology, the following four different schemes (SC) are analyzed.

SC1: Operation scheduling of the EV is exclusively analyzed with and without battery degradation cost

SC2: Coordinated operation scheduling of EV and BESS is analyzed with and without battery degradation cost

SC3: Operation scheduling of only BESS is analyzed with and without battery degradation cost while EV's charging schedule is uncoordinated

SC4: No scheduling is applied and EV's charging schedule is uncoordinated

The proposed MINLP is solved for 1000 scenarios in GAMS software. The problem consists of 76,000 continuous variables, 76,000 binary variables, and 286,000 constraints, and it is solved on an Intel(R) Core (TM) i5-8250U CPU @ 1.60 GHz (4 CPUs), RAM 8 GB system in 11 min. Despite the large scale of the problem, it is easy to solve since it is quite close to a linear function. The probability distributions of EV's and BESS's state of charge (SOC) in different maximum charge-discharge rates of EV for the second scheme are demonstrated in Fig. 6 by three-dimensional boxplot concept. The electricity procurement cost, battery degradation cost, and total cost for different schemes are summarized in Table 2. To take a closer look into the functionality of the optimization process in different schemes, SOC of the EV, and BESS for the forecasted scenario are demonstrated by Fig. 7.

As can be seen, in Fig. 6 whenever the degradation cost is ignored, the boxplots have many ups and downs. That is to say, both EV and BESS undergo many charge-discharge cycles to exploit battery capabilities as much as possible. On the other hand, when the battery degradation cost is included in the problem, the boxplots are not only shorter, but also their variations is considerably smaller. These phenomena are strict measures taken by the algorithm to reduce battery degradation and to use battery only when it is economically viable. Moreover, the maximum SOC level of BESS is significantly restricted to lower SOC values. Since final SOC of the BESS is fixed, it is a legitimate decision to not charge BESS to high levels of SOC due to the fact that battery gets degraded.

The previously mentioned observations on boxplots can be further substantiated by SOC curves on Fig. 7. As it is revealed, whenever the degradation cost is waivered, both EV and BESS undergo multiple charge-discharge cycles. Whereas, with degradation cost, there is only one observable cycle. Furthermore, the higher charging rates results in deeper cycle depths. Because higher charging rates provide more maneuver space for the algorithm; for instance, when the charging rate is set to 5 kW, EV should be charging for at least 5 h. Nevertheless, 2.5 h is sufficient when the charging rate is set to 10 kW. Hence, it can take maximum benefits from opportunities provided in the price-wise expensive hours of the day. In the uncoordinated scheme, EV gets charged as soon as it arrives. Consequently, SOC rises steadily until the full charge is achieved. In SC2-WD (WD denotes with degradation cost) when the charging rate of EV is 5 kW, the BESS discharges more in comparison to the state where EV's charging rater is 10 kW. The reason is the inabilities of EV at lower charging rates which is compensated by

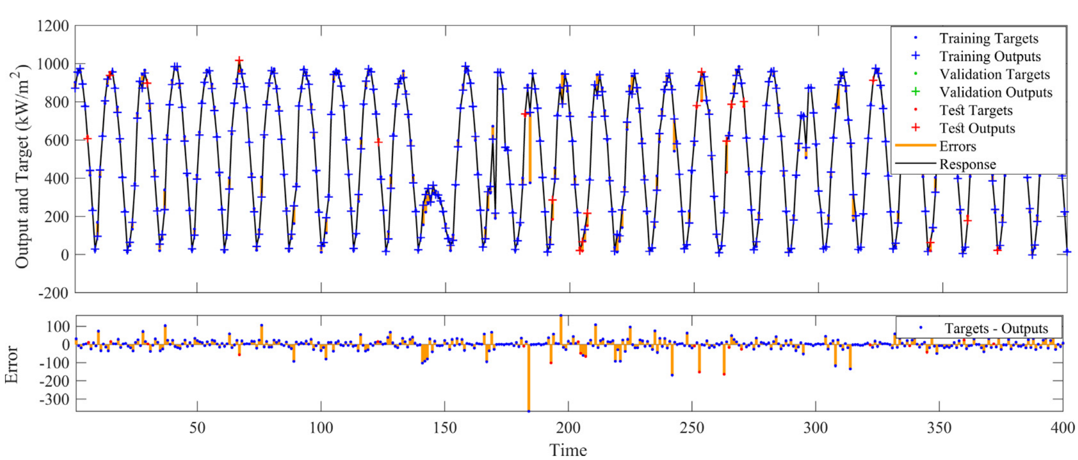

Fig. 4. The response of ANN-based time series prediction for solar irradiation.

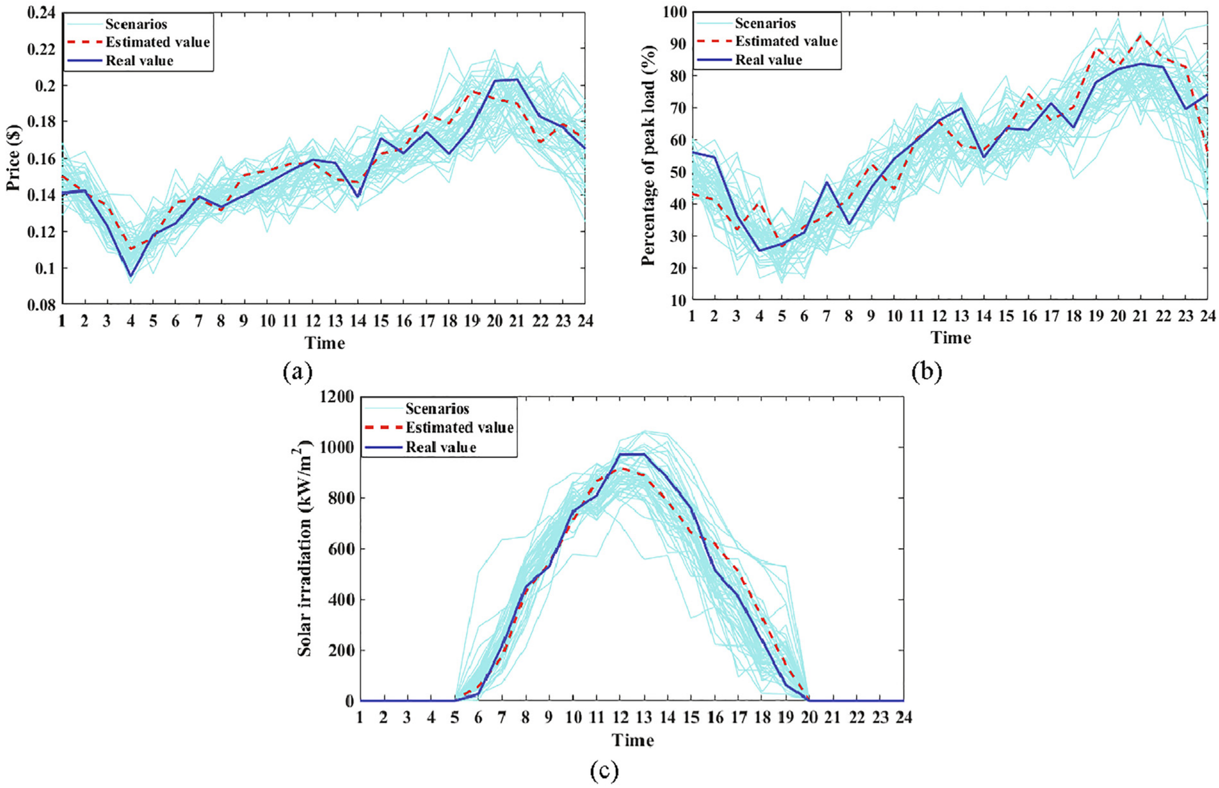

Fig. 5. The generated scenarios, estimated values and forecasted values: (a) electricity price (b) residential load demand (c) solar irradiation.

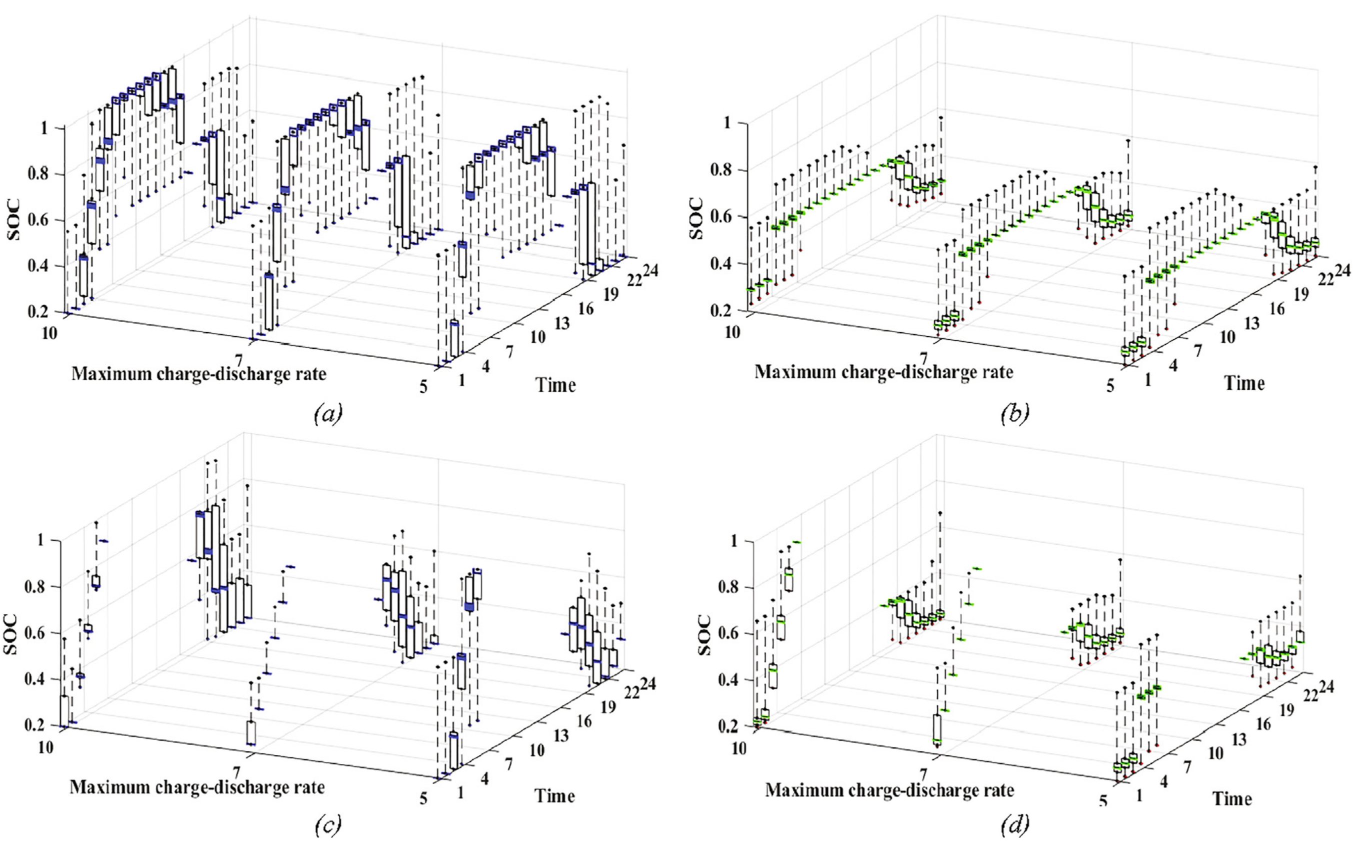

Fig. 6. SOC distribution in SC2: (a) BESS without degradation (b) BESS with degradation (C) EV without degradation (d) EV with degradation.

Table 2
Different cost aspects of each scheduling scheme.

Charge-discharge rate		Scheme						
		SC1	SC1-WD	SC2	SC2-WD	SC3	SC3-WD	SC4
Cr_{EV} = 5	Electricity Cost ($)	2.196	2.831	0.194	1.905	1.511	2.945	4.459
	Deg_{EV} ($)	1.179	0.110	1.178	0.109	–	–	–
	Deg_{BESS} ($)	–	–	6.300	0.471	6.301	0.474	–
	Total Cost ($)	3.375	2.941	7.672	2.485	7.812	3.419	4.459
Cr_{EV} = 7	Electricity Cost ($)	2.073	2.456	−0.238	1.530	1.385	2.789	4.531
	Deg_{EV} ($)	2.498	0.225	2.007	0.222	–	–	–
	Deg_{BESS} ($)	–	–	6.280	0.468	6.300	0.468	–
	Total Cost ($)	4.571	2.681	8.049	2.220	7.685	3.257	4.531
Cr_{EV} = 10	Electricity Cost ($)	1.613	2.169	−0.595	1.375	1.357	2.807	4.437
	Deg_{EV} ($)	5.058	0.309	5.094	0.308	–	–	–
	Deg_{BESS} ($)	–	–	6.160	0.347	6.299	0.353	–
	Total Cost ($)	6.671	2.478	10.659	2.03	7.656	3.160	4.437

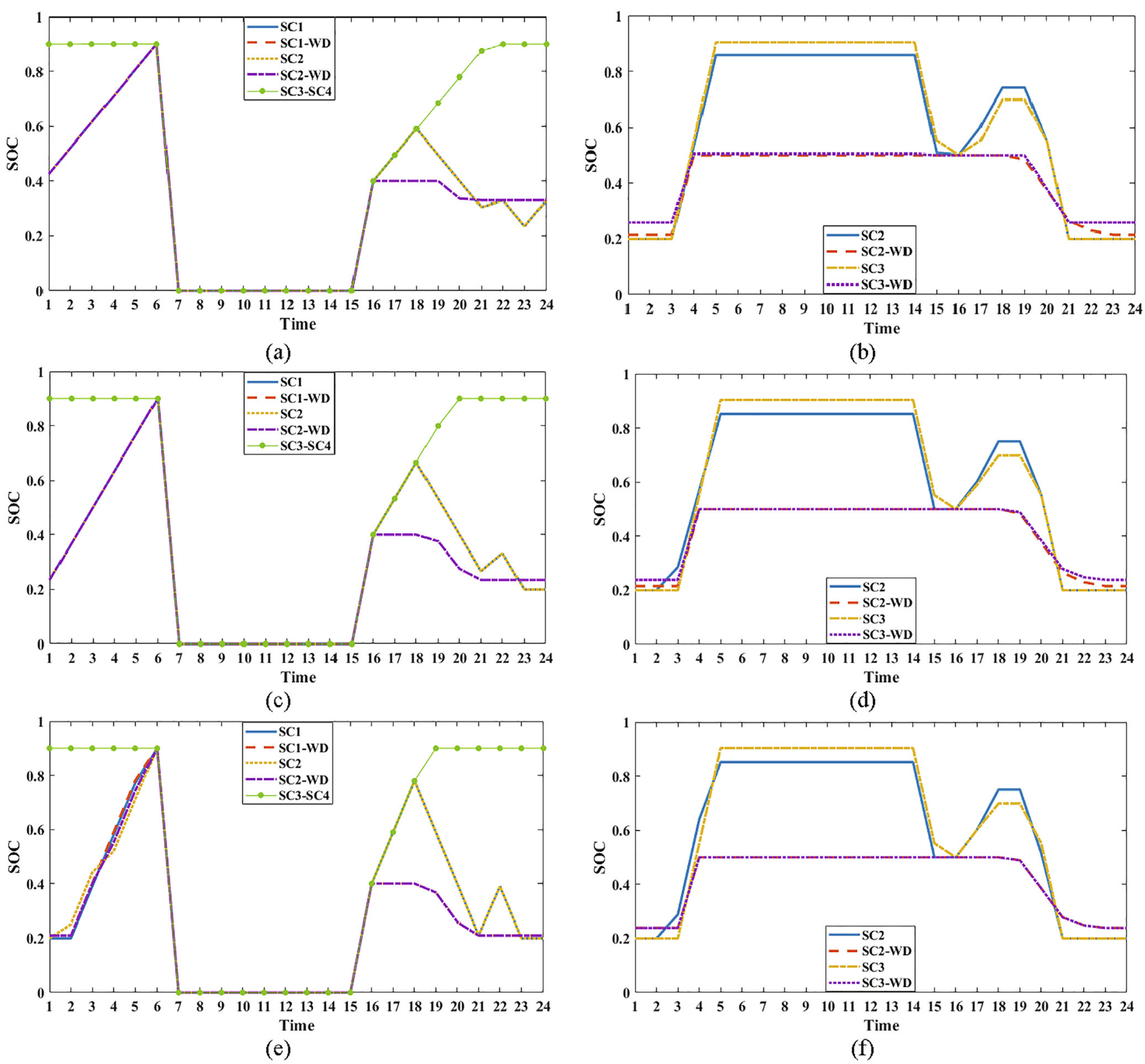

Fig. 7. SOC value of EV and BESS for different charging rates of EV: (a) SOC of EV for Cr_{EV} = 5 (b)SOC of BESS for Cr_{EV} = 5 (c)SOC of EV for Cr_{EV} = 7 (d) SOC of BESS for Cr_{EV} = 10 (e) SOC of EV for Cr_{EV} = 10 (f) SOC of BESS for Cr_{EV} = 10.

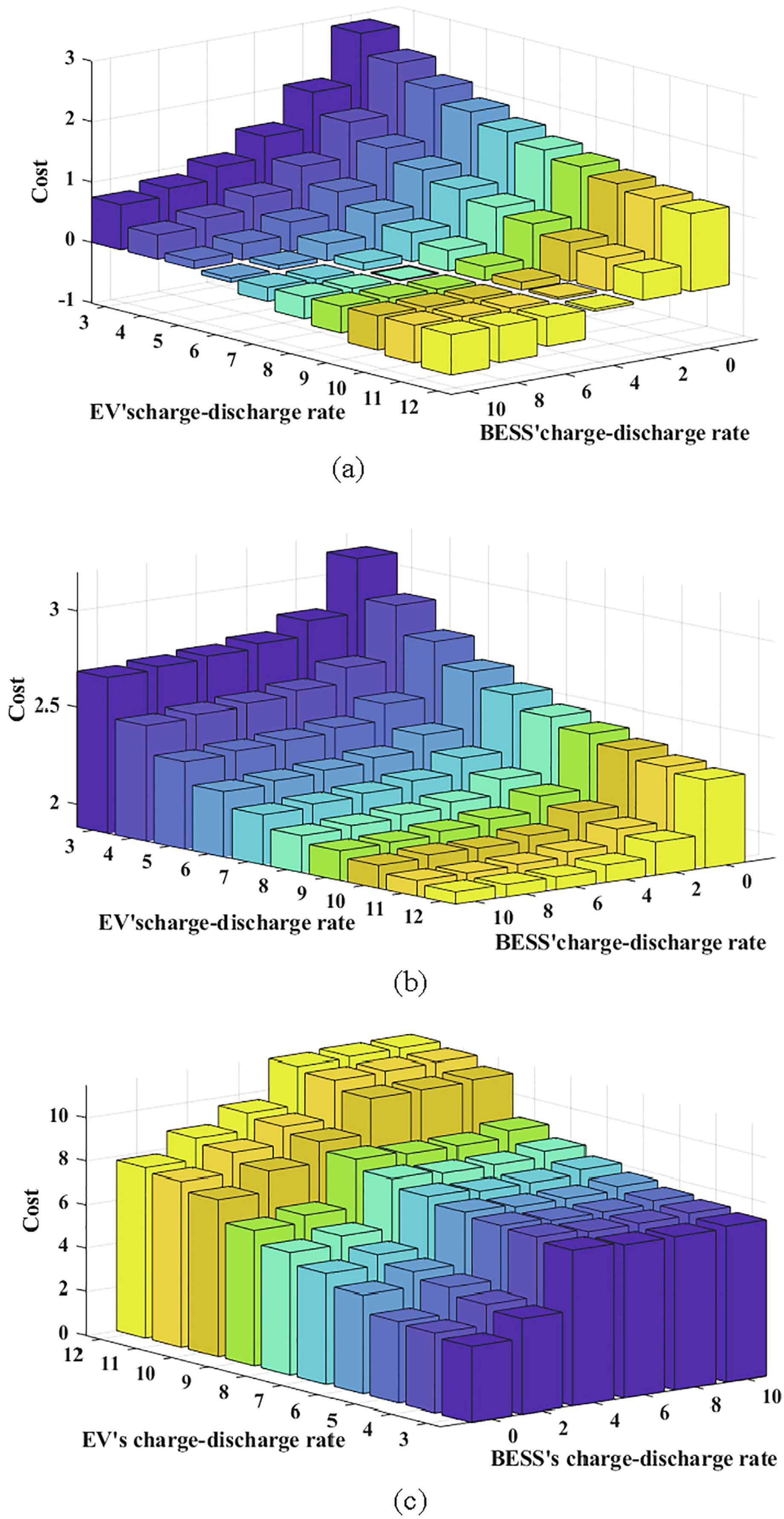

Fig. 8. Sensitivity diagram of cost in SC2 for different maximum charge-discharge rates of EV and BESS: (a) objective cost when degradation cost is ignored (b) objective cost when degradation cost is included (c) actual cost when degradation is ignored.

Table 3
Value of stochastic solution in different schemes.

Scheme	Charge-discharge rate		
	$Cr_{EV} = 5$	$Cr_{EV} = 7$	$Cr_{EV} = 10$
SC1	1.252	0.916	0.976
SC1-WD	0.811	0.803	0.806
SC2	0.896	0.937	1.068
SC2-WD	0.831	0.816	0.817
SC3	0.2	0.209	0.215
SC3-WD	0.013	0.012	0.025
SC4	0	0	0

BESS. Based on this behavior, it can be intuitively hypothesized that higher charging rates of EV reduce the strain on BESS. This hypothesis can be proved by the results stated in Table 2. In simple words, increasing EV's charging rate reduces the BESS cycle degradation, and both components get degraded in a more equilibrated way. Moreover, As can be seen from Table 2, ignoring battery degradation cost can be highly deceptive. By focusing only on the electricity bill, it is tempting to ignore degradation. The results, however, are quite self-explanatory. Especially at higher charging rates, the degradation cost is disproportionally more than the electricity cost. In SC1-WD the optimization is restricted to the availability hours of EV. Whereas, in SC2-WD, EV and BESS provide considerably lower cost by cooperatively shifting household's and EV's load demand to the cheaper hours of the day. Similarly, in SC3-WD the EV gets charged uncoordinatedly at peak load hour with high electricity cost and BESS cannot shift this great load to the cheaper hours of the day. Hence, SC2-WD is the most profitable scenario. SC1-WD proves to be more effective then SC3-WD. The reason is that EV requires a great load demand which can be simply shifted by changing the charging hours of the EV, while in SC3-WD, the BESS should shift this great load in discharging cycle which imposes high degradation cost. For this particular reason, SC1-WD has less cost than

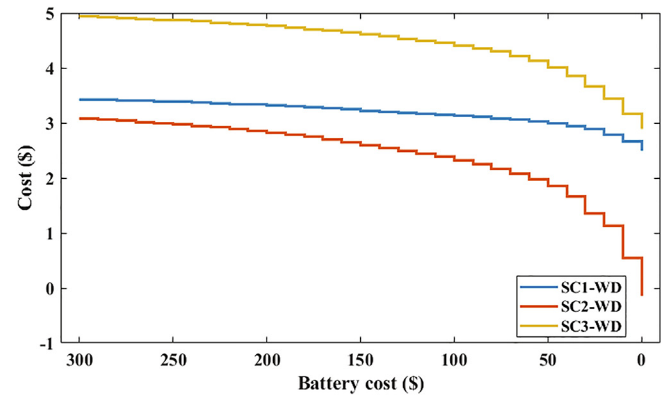

Fig. 10. Effects of battery cost reduction in future market on the problem.

SC3-WD. Because, when the degradation cost is ignored, BESS can take the burden of EV's load demand, and since it does not have the availability limitations of EV, it can simultaneously shift the household's and EVs load demand. Consequently, in SC3 electricity provision cost is less than SC1. As can be guessed, SC4 imposes the highest electricity procurement cost since EV uncoordinatedly gets charged at peak hours and there is no equipment to shift the household's load demand.

To observe the effect of maximum charging rate on the problem, a sensitivity analysis is implemented by setting different maximum charge-discharge rates for EV and BESS in SC2. The results are illustrated by bar-plots in Fig. 8. It is evident that when the degradation cost is included, increasing EV's maximum charge-discharge rate is more effective than increasing the BESS charging rate. The reason is that the initial SOC of the BESS is equal to its final SOC. Hence, it does not impose any load on the system. On the other hand, EV should be charged to sufficient amount of SOC until departure time and higher charging rates facilitate shifting this huge load by simply charging in

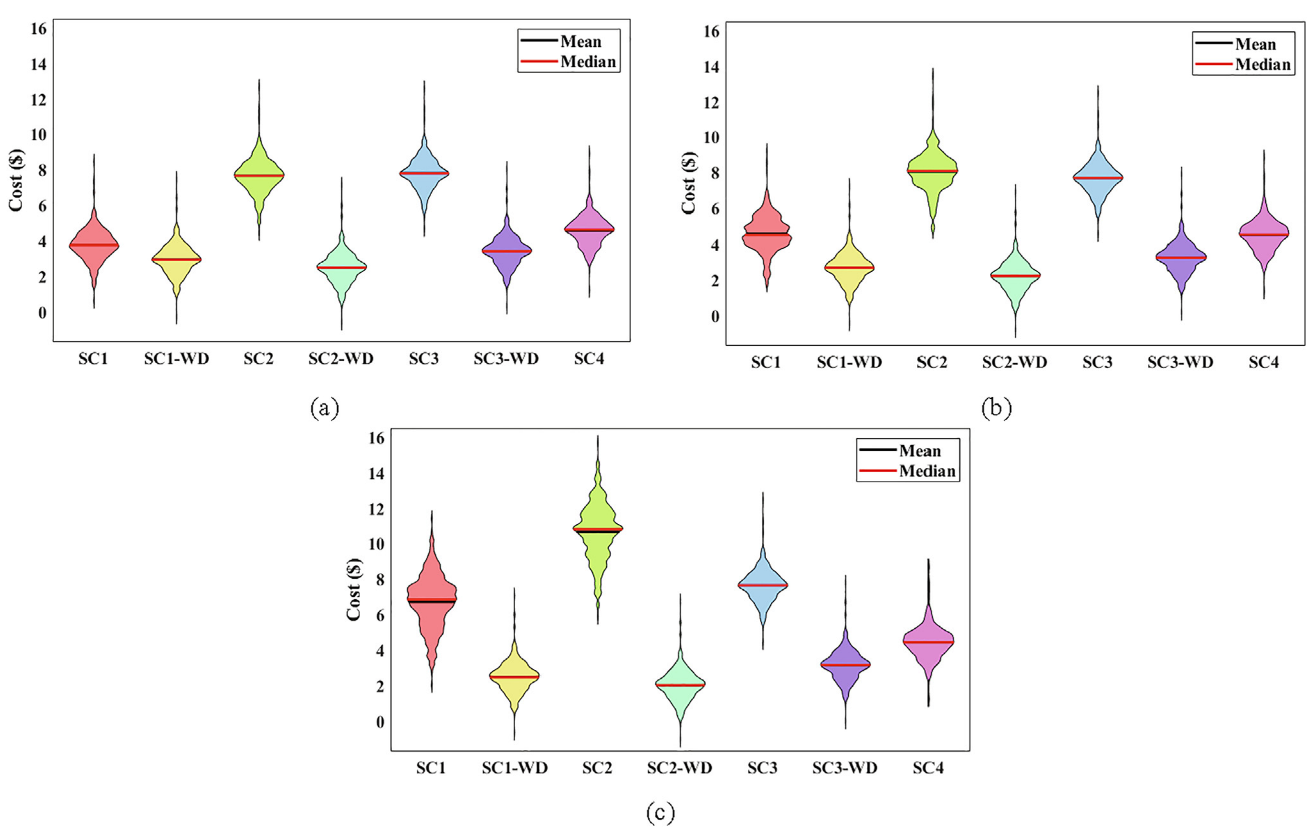

Fig. 9. Probability distribution of the cost function for different schemes: (a) $Cr_{EV} = 5$ (b) $Cr_{EV} = 7$ (c) $Cr_{EV} = 10$.

cheaper hours of the day. When the battery degradation is disregarded, both EV and BESS have almost equal sensitivity on the electricity procurement cost since the discharging half-cycle does not impose extra costs. On the contrary, when the degradation cost is taken into account, the actual cost inflicted upon the household rises steeply with the maximum charging rate, and it is considerably more than the provided service.

To evaluate the effectiveness of the stochastic programming method, the value of stochastic solution (VSS) is calculated by (17), and it is summarized in Table 3 for different schemes with and without degradation cost.

$$VSS = Z^D - Z^S \tag{17}$$

To calculate the objective function in deterministic case (Z^D), the objective function is firstly solved for the deterministic scenario where all the random input variables are set equal to their expected values. Then, the stochastic variables in different scenarios are fixed to this deterministic result and the stochastic objective function is resolved. The difference between the results of this objective function with fixed variables and the primary stochastic objective function signifies VSS. In fact, the VSS is the amount extra cost which user should pay for not using stochastic programming method. The value of VSS is particularly low in SC3 and SC4 since in these scenarios EV's charging is uncoordinated, and it is a fixed variable even in the main problem. The amount of VSS might seem trivial, but in the long-term, it can add up to a great deal of income losses.

Fig. 9 illustrates the probability distribution of the objective function in violin-plot concept for different scenarios with and without battery degradation cost with different charging rates. It should be noted that, to evaluate the objective function in different schemes under the same scale, the battery degradation cost is separately calculated for the schemes without degradation cost and it is added to the objective value. The probability density distribution of the cost in different schemes validates the previously demonstrated results in Table 2. As can be seen, the SC2-WD is distributed in the lowest-cost areas, while all scenarios which do not include the battery degradation are distributed in high-cost regions which variate according to different charging rates. Furthermore, increments in charging rate reduces the total cost when battery degradation is included in the problem. Whereas, when the degradation is ignored, increments in charging rate increases the total cost.

To have a more in-depth insight into the effects of battery cost reductions in future market, the problem is solved numerous times by reducing battery cost consecutively. The results are depicted by Fig. 10 for different schemes, while Cr_{EV} is set equal to 10 kW. As it is shown, the cost reduction nonlinearly affects the objective function. Obviously, SC1-WD has the lowest sensitivity for cost reduction since SC1-WD mostly schedules the charging cycle of EV, which does not enforce degradation cost. The SC2-WD is the most sensitive case considering that it has both EV and BESS. In SC3-WD the EV's charging pattern is uncoordinated. Hence, BESS should shift this considerable load to the off-peak hours, which is not economically viable. Nonetheless, as the battery storage cost gets lower, the BESS can take over the responsibility of scheduling the EV and SC3-WD gets closer to SC1-WD. Similarly, when the battery storage cost is very high, SC2-WD and SC1-WD are close to each other since BESS is not economical to use BESS.

Conclusion

This study investigated the stochastic scheduling of HEMS from different points of view, such as, battery degradation cost, inherent uncertainties, and parameter sensitivity. An ANN-based scenario generation method is incorporated into the problem. the error time series of the predicted scenarios proved the legitimate accuracy of the proposed method. Furthermore, different scheduling schemes were carefully inspected. The results showed that the cooperative scheduling of BESS is the most profitable scheme and the uncoordinated charging scheme imposes the highest electricity procurement cost. Additionally, it is confirmed that ignoring battery degradation increases the total cost to an unacceptably high level. The maximum charging rate sensitivity analysis demonstrated that the cost function is more sensitive to EV's charging rate in comparison with that of the BESS. The battery cost analysis proves that battery cost reductions in the future market will non-linearly increase the economic viability of the system. The value of stochastic solution proves the efficiency of the stochastic programming method in comparison with the deterministic case. Eventually, it is observed that the cooperative operation of EV and BESS decreases the total degradation. That is to say, the system degrades the component which has more economic viability. Therefore, as a prospect for future studies, optimal scheduling of multiple EVs and BESSs of a green neighborhood could be studied considering battery degradation cost. Because, in some scheduling occasions, it might be more economical to the degrade neighbors BESS or EV, and then compensate for their degradation cost.

CRediT authorship contribution statement

Saeed Zeynali: Conceptualization, Methodology, Software, Validation, Data curation, Formal analysis, Investigation, Writing - original draft. **Naghi Rostami:** Conceptualization, Visualization, Supervision, Project administration, Investigation, Writing - original draft. **Ali Ahmadian:** Visualization, Supervision, Project administration, Investigation, Writing - original draft. **Ali Elkamel:** Supervision, Project administration, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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