Abo-Elyousr, Farag K.; Sharaf, Adel M.; Darwish, Mohamed M.F.; Lehtonen, Matti; Mahmoud, Karar

Optimal scheduling of DG and EV parking lots simultaneously with demand response based on self-adjusted PSO and K-means clustering

Published in:
Energy Science and Engineering

DOI:
10.1002/ese3.1264

Published: 01/10/2022

Document Version
Publisher's PDF, also known as Version of record

Received: 4 April 2022 | Revised: 19 July 2022 | Accepted: 20 July 2022

DOI: 10.1002/ese3.1264

ORIGINAL ARTICLE

Optimal scheduling of DG and EV parking lots simultaneously with demand response based on self-adjusted PSO and K-means clustering

Farag K. Abo-Elyousr[1] | **Adel M. Sharaf**[2,3] | **Mohamed M. F. Darwish**[4,5] | **Matti Lehtonen**[4] | **Karar Mahmoud**[4,6]

[1]Department of Electrical Engineering, Faculty of Engineering, Assiut University, Assiut, Egypt

[2]Sharaf Energy Systems, Inc., New Maryland, New Brunswick, Canada

[3]Intelligent Environmental Energy Systems, Canada Inc. of Fredericton, New Brunswick, Canada

[4]Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, Espoo, Finland

[5]Department of Electrical Engineering, Faculty of Engineering at Shoubra, Benha University, Egypt

[6]Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan, Egypt

Correspondence

Mohamed M. F. Darwish, Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, Espoo 02150, Finland.
Email: mohamed.m.darwish@aalto.fi and mohamed.darwish@feng.bu.edu.eg

Farag K. Abo-Elyousr, Department of Electrical Engineering, Faculty of Engineering, Assiut University, Assiut 71516, Egypt.
Email: farag@aun.edu.eg

Karar Mahmoud, Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, Espoo 02150, Finland.
Email: karar.mostafa@aalto.fi

Abstract

Recently, the proliferation of distributed generation (DG) has been intensively increased in distribution systems worldwide. In distributed systems, DGs and utility-owned electric vehicle (EV) to grid aggregators have to be efficiently scaled for cost-effective network operation. Accordingly, with the penetration of power systems, demand response (DR) is considered an advanced step towards a smart grid. To cope with these advancements, this study aims to develop an innovative solution for the day-ahead sizing approach of energy storage systems of EVs parking lots and DGs in smart distribution systems complying with DR and minimizing the pertinent costs. The unique feature of the proposed approach is to allow interactive customers to participate effectively in power systems. To accurately solve this optimization model, two probabilistic self-adjusted modified particle swarm optimization (SAPSO) algorithms are developed and compared for minimizing the total operational costs addressing all constraints of the distribution system, DG units, and energy storage systems of EV parking lots. The K-means clustering and the Naive Bayes approach are utilized to determine the EVs that are ready to participate efficiently in the DR program. The obtained results on the IEEE-24 reliability test system are compared to the genetic algorithm and the conventional PSO to verify the effectiveness of the developed algorithms. The results show that the first SAPSO algorithm outperforms the algorithms in terms of minimizing the total running costs. The finding demonstrates that the proposed near-optimal day-ahead scheduling approach of DG units and EV energy storage systems in a simultaneous manner can effectively minimize the total operational costs subjected to generation constraints complying with DR.

KEYWORDS

demand response, electrical vehicles, K-means clustering, Naive Bayes approach, objective function, optimal scheduling, particle swarm optimization

1 INTRODUCTION

Recently, the use of resilient distributed generations (DG) aggregators in distribution systems has been rapidly increasing. With the penetration of vehicle to utility-owned grid (V2G) aggregators to the grid, demand response (DR) has a significant role in effectively utilizing the demand side resources due to the constraints related to conventional distributed generators.[1] Besides this, the significant improvements in smart grid communication enable system designers and developers to develop DR with the optimal format. By definition, DR response is related significantly to the final customer electric consumption changes in comparison to the ordinary usage patterns.[2] For this definition, electric vehicle (EV) owners and DR primary agents are considered customers. For these customers, an efficient impact on the power system is expected. They can improve the day-ahead system reliability and decrease total operational costs by voluntary management of load demands and DR.[2,3] On the other hand, there are a number of aspects of the contemporary power systems that make the V2G optimization inadequate for the charging/discharging of EVs. These characteristics include (i) The widespread utilization of renewable energy sources, which are uncertain and intermittent. (ii) Typically, conventional optimization techniques are nonlinear, thus discovering a global minimum in a multi-energy resources system might not be assured. (iii) At the parking lot, V2Gs establish random day-ahead scheduling with different time energy costs, charger capacities, and charging/discharging regulations, (iv) future proposals and potential validations for future smart grids are required due to the energy demand's rising complexity, which is worsened by the advent of particular load fluctuations such V2G and DR impacts. Consequently, the authors of this study are motivated to develop a novel modified effective day-ahead scheduling technique to handle all such issues for the purpose of minimizing overall expenses while maintaining a degree of customer satisfaction that is acceptable.

DR can be modeled using the elasticity matrix of the electricity prices of the load demands.[4,5] Using a constant elasticity matrix over a pre-determined period of time, it was concluded by various studies[6–11] that DR has a significant positive impact on the electricity market prices, reliability, and spinning reserves issues. However, this assumption of fixed elasticity of specific over specific time results in the incredibility of EVs of the proposed methods.[1] With the modern penetration of EVs into the grid, the scheduling of DR has become more complicated due to a lack of information on the demand characteristics patterns. For this reason, DR program operators inquire information from the final consumer for better credibility.[12] Demand resources require initial information from the customer to participate effectively in the DR program. In the study by Asadinejad et al.,[13] the evaluation of DR is evaluated using the elasticity and fabrication matrices. The regression modes for DR were introduced by Srivastava et al.[14] An optimal scheduling approach for DR within smart grids was introduced by Nan and Zhou.[15] In the study by Viana et al.,[16] DR with renewable photovoltaic generation was discussed. Similar work with energy hub optimization was presented by Huo et al.[17]

Several metaheuristic algorithms were used to solve the economic dispatch with DR aspects.[18] Yet, particle swarm optimization (PSO) has been reported to have a remarkable exploitation feature.[19] Elnozahy et al.[19] utilized this feature to enhance other metaheuristic algorithms. In the study by Goudarzi et al.,[20] it was combined with an artificial bee colony for vertical handover in wireless networks. It was combined with a genetic algorithm (GA) to optimize total costs for a hybrid wind-PV battery system in the study by Ghorbani et al.[21] It was developed by Sharaf et al. to improve wind energy conversion dynamics, permanent magnet synchronous motor performance, and other power system issues.[22–24] PSO was employed successfully for solving DR issues in various studies.[25,26] PSO exploration ratio, on the other hand, does not have the same repute as the exploitation feature. This motivates the authors of this study to develop two probabilistic self-adjusting metaheuristic algorithms based on PSO optimizer to solve the generation and DR with V2G impact. In this manner, the exploration feature would benefit from the self-adjustment and converge fast towards the near-optimal solution.

Over time, EV penetration into the utility grid acquires more intention. In the study by Gough et al.,[27] an economic feasibility study was done. The authors concluded that V2G could provide a significant income if V2G was coordinated properly. A study done[28] was achieved by using V2G impact to minimize total emissions with microgrid energy scheduling. Optimal scheduling of EVs was carried out in the study by Mortaz and Valenzuela[29] at the microgrid level, where various control strategies for enhancing the operation of microgrids connected to energy storage systems were introduced in various studies.[30–34] The optimal charging management was investigated by Mkahl et al.[35] Similar work was achieved by Bin-Humayd and Bhattacharya.[36] The parking coordination of EVs was investigated in the study by Faddel et al.[37] The investigation of the above research[2–13,15–17] reveals that a constant elasticity matrix for a specific interval of time was used, which results in some incredibility. In the study by Srivastava et al.,[14] regression methods generally need training, and the accuracy of the regression models depends on the number of available data. Furthermore, the impact of V2G was not addressed.[1,17] The investigation of various studies[27–37] show that they did not include DR in V2G research studies. This encourages the authors of the current study to develop optimal day-ahead scheduling of utility-owned V2G combined with DR, which is rare in the literature.

To cover the above-mentioned research gaps, the goal of this study is to provide an optimal simultaneous hourly scheduling strategy for energy storage systems of EV parking lots and distributed generators in smart distribution networks that conform with DR. The suggested solution is unique in that it allows interactive consumers to engage successfully in power systems. Two self-adjusted particle swarm optimization (SAPSO) methods are devised and compared to minimize overall operational costs while addressing all restrictions of the distribution system, DG units, and energy storage systems of EV parking lots. In particular, this study contributes to the literature as follows: (i) two modified probabilistic metaheuristic algorithms integrated with the K-means clustering approach based on conventional PSO are developed so that both the exploration and exploitation features of the conventional PSO are enhanced. In both optimizers, the Naive Bayes classifier is employed to investigate the day-ahead EVs to participate efficiently in the DR program. Furthermore, the DR and V2G demand is converted into a virtual generation whose marginal cost function is that of the load reduction. The K-means clustering, which is an unsupervised machine learning approach, is used to find the EVs that are ready to engage in the DR program effectively. (ii) Optimal scheduling subjected to constraints of generation DR with V2G is developed by minimizing system total operational costs. In turn, the validation of the developed optimizers is demonstrated through an impartial comparison with the conventional PSO and GA optimizers. The SAPSO optimization techniques created to solve the model's nonlinearity and non-convexity are based on dynamic error adjustments of the weightings, speed deviations, and position equations. In contrast to the traditional PSO, corrective action is developed in terms of errors and rate of change. To validate the efficacy of the created algorithms, the acquired results on the IEEE-24 reliability test. According to the results, the first SAPSO algorithm beats the other algorithms in terms of lowering total running expenses. It is revealed that the suggested optimum scheduling methodology for DG units and EV energy storage systems may successfully decrease total operating costs while complying with DR generation limits.

The remaining of this manuscript is organized as follows. Problem description and formulation are introduced in Sections 2 and 3, respectively. The simulated results are given in Section 4. Finally, the discussions and conclusions are presented in Sections 5 and 6, respectively.

2 | PROBLEM DESCRIPTION

Figure 1 shows the structure of modern distribution systems in which various distributed energy sources and EVs are distributed along with smart meters that are utilized for DR. Accordingly, this study concerns the DGs and DR with V2G optimal scheduling. The current electric microgrids are undergoing a change as distributed energy resources, including infrequent renewable production resources on the distribution side, become more and more integrative. Therefore, if effective day-ahead scheduling of DGs is adequately coordinated, there would be real benefits for both utilities and their consumers.

2.1 | System description

The study brings together the formulation of optimal scheduling of generation and DR. The considered IEEE 24-bus system includes DGs, DR with V2G to minimize total operational costs. DR is transformed into virtual generation units. The modeling of the costs of the individual components is presented in the following sections. The objective function is to reduce DG, DR, and V2G costs. In the subsections that follow, each of these costs is mathematically expressed.

2.1.1 | Cost modeling of distributed generating units

Considering the DG unit status, the total costs of a generating unit are given in (1) in terms of its output power.[2,38–40] Table A1 gives the parameters at the corresponding buses for estimating the total operational costs.[1,41]

$$C_g^i\left(P_g^i(t)\right) = \alpha^i\left(P_g^i(t)\right)^2 + \beta^i\left(P_g^i(t)\right) + \gamma^i s^i(t) + STC^i b^i(t) \quad \forall\ t \in T \text{ and } \forall\ i \in G, \tag{1}$$

where T presents the set of day-ahead hourly periods, G is the set of generating units, C_g^i is the operational cost of a generating unit, P_g^i is the output power of a generating

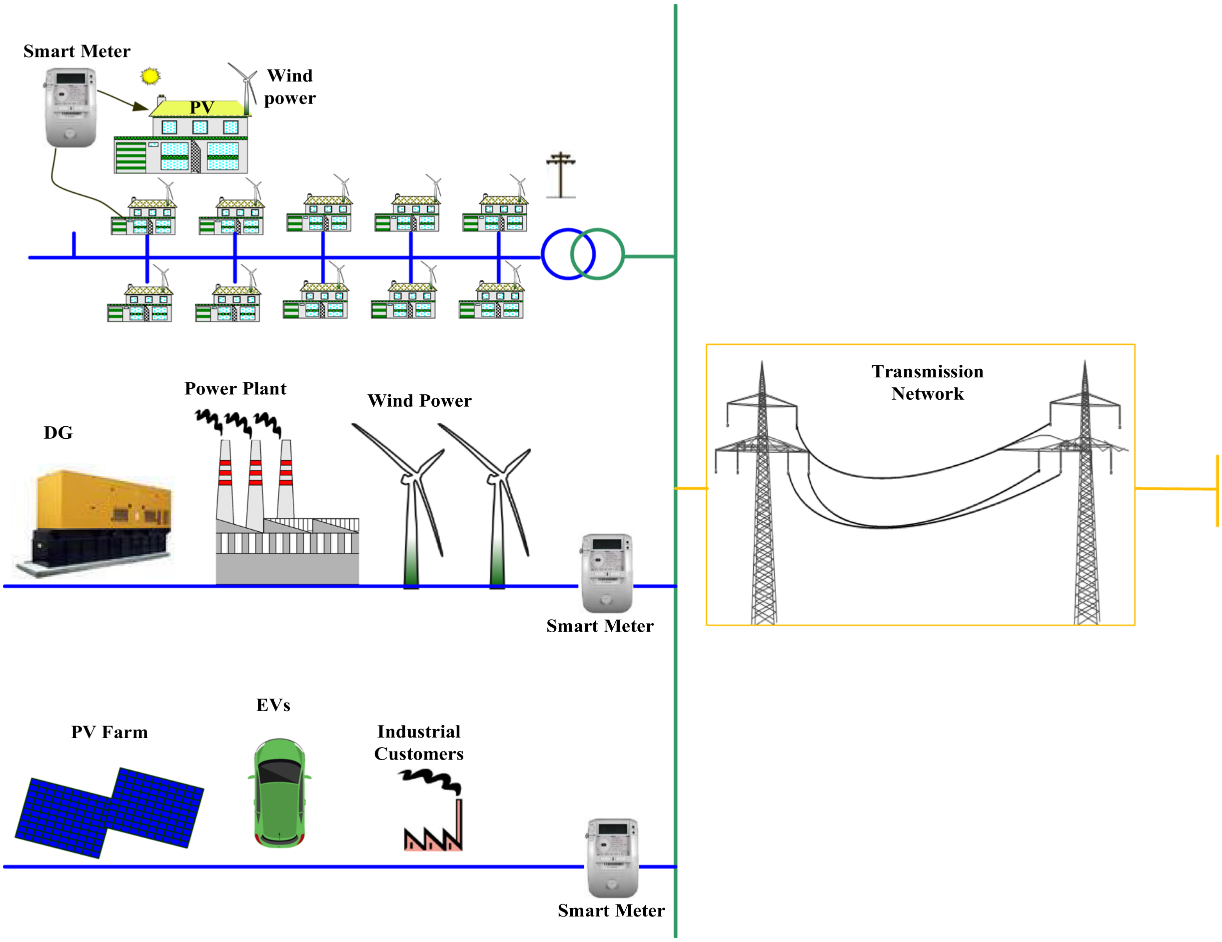

FIGURE 1 Modern distribution system. DG, distributed generation; EV, electric vehicle.

unit, s^i is unit commitment flag $\in \{0,1\}$, STC^i is the startup cost of unit i, and b^i is starting flag of a unit.

2.1.2 | Cost modeling of DR units

Customers were asked to supply basic information to participate successfully in the DR program. Besides, the DR program collects the required historical data based on the responsive nature of a customer. However, there is some information necessary to express the DR costs. The first is the maximum reduction power M^j in megawatts that a customer j can bear. The second is the duration at which a customer j is available. The third is the number of yearly participation or frequency of a customer. With the above information and the relevant parameters in Appendix section, the DR costs of a customer j are expressed as in (2).[1,2,42] The parameters α^j and β^j depend on the DR marginal cost as will be explained in the problem formulation section. The key finding is to find the virtual resource $DR(t)$ so that an objective function is satisfied.

$$C_{DR}^{j}(DR^j(t)) = \alpha^j (DR^j(t))^2 + \beta^j (DR^j(t)) \quad \forall\ t \in T \ \text{ and } \ \forall\ j \in DRG, \tag{2}$$

where C_{DR}^{j} presents the operational cost of a generating unit, DR^j represents the output power of a demand resource unit, and DRG is the set of demand resource units.

2.1.3 | Cost modeling of V2G units

V2G energy storage batteries are probabilistic in nature. It depends on the state of charge (SOC) for an EV to be a load or demand resource. The DR cost of a V2G is basically related to the on-gird battery operational costs and expressed as follows[43]:

$$C_{V2G}^{k}(V2G^k(t)) = \beta^k (V2G^k(t)) \ \forall\ t \in T \ \text{ and } \ \forall\ k \in V2GR, \tag{3}$$

where C_{V2G}^{k} describes the operational cost of a V2G unit in \$/kWh, $V2G^k$ describes the output power of a V2G demand resource unit, and *V2GR* describes the set of demand resource units.

2.2 | Overview self-adjusting PSO

Conventional PSO utilizes stochastic solutions, which makes the derivative information for conversions long. SAPSO utilizes different approaches to speed up the conversion process. In the following, a brief overview of the conventional PSO is presented. Then, the required improvements for the developed SAPSO are investigated.

Conventional PSO requires a few numbers of parameters to be adjusted.[44] It was inspired to imitate animals' and birds' movement behavior.[19,20,45] The particles are distributed randomly. The particle positions contain the decision variables. Besides, each particle represents a possible solution. The particle decision variables and the corresponding fitness value is defined by a position and a fitness function. The particles proceed in a recursive issue to calculate the optimal decision variables according to the fitness function.

The position of a particle (P_k) is modeled by a location in the *XY* plane as shown in Figure 2. The particle velocity is represented by V_x and V_y in the *x*-axis and *y*-axis, respectively. The particle collection in the *XY* plane is explored by a pest value (P_{best}). Among the group of P_{best} values, a global best (g_{best}) is required. The particle's position is updated according to (4).[46]

$$WV_{\text{new}} + c_1 r_1 (GB - CP) + c_2 r_2 (PB - CP), \tag{4}$$

where V_{new} is the new velocity of the particle's position change, *W* is the Inertia weight, *GB* is the global best, *PB* is the personal best, *CP* is the current position, r_1 and r_2 represent the two random variables, c_1 is the global learning coefficient, c_2 is the personal learning coefficient. Hence, the procedures for PSO are as follows:

1- The system is started by defining a population of random solutions. The optimization problem is formulated by random velocity. Each potential solution with a velocity is recognized as a particle.
2- Within the population, the fitness function is evaluated.
3- For every iteration, P_{best} is recorded.
4- The particle's best solution (P_{best}) within the population is compared with other populations and swarm global best (g_{best})is determined.
5- The velocity of a particle is updated.
6- The steps from 2–5 are repeated till a maximum number of iterations ($N_{\max}$) is reached.

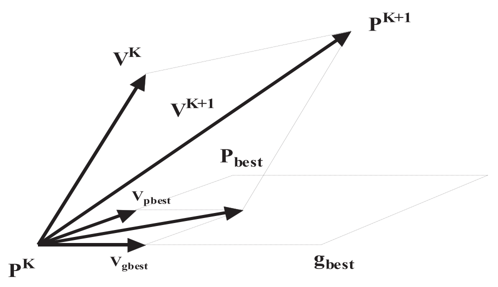

FIGURE 2 Particle position concept by particle swarm optimization.

The developed SAPSO algorithms suggest a modification for the inertia weight given in (1). The value of the inertia weight is adjusted based on the error estimation in each iteration. Two algorithms are developed in this study.

2.2.1 | SAPSO#1

In this algorithm, the inertia weight is calculated using the following equations from (5) to (7). The error estimation in (5) represents the g_{best} improvement. Using the normalized error (ξ_k) given in (6), the inertia weight (W_k) is updated according to (7).

$$\Delta e_k = GB_{k-1} - GB_{k-2}, \tag{5}$$

$$\xi_k = \frac{\Delta e_k}{\max(GB_k)}, \tag{6}$$

$$W_k = W_0 \times (1 + \xi_k) \times (k - 1)/d. \tag{7}$$

With *k* being the iteration number index, the particle position (X_{new}) is updated through the following equations. In (9), d_0 is a design parameter between 10 and 100. The variable (D_k) is used to obtain the new position of particles in terms of their velocity as in (10).

$$\eta_k = \frac{GB_{k-1}}{\max(GB_k)}, \tag{8}$$

$$D_k = d_0 \times (1 + \eta_k), \tag{9}$$

$$X_{\text{new}} = X_{\text{old}} \times D_k + V_{\text{old}}. \tag{10}$$

2.2.2 | SAPSO#2

In this algorithm, two parameters are introduced (α_k and β_k) according to (11) and (12). The inertia weight factor in this algorithm is evaluated according to (13) based on α_k and β_k in terms of the global best during each iteration.

$$\alpha_k = GB_k - GB_{k-1}, \tag{11}$$

$$\beta_k = \alpha_k - \alpha_{k-1}, \tag{12}$$

$$W_k = \frac{W_o(1 + \alpha_k + \beta_k)}{\max(GB_k)}. \tag{13}$$

2.3 | K-means clustering

K-means clustering is an unsupervised machine learning approach that tries to group comparable observations into clusters to aid in determining if V2G status is a load or a power resource. It attempts to divide the data into groups with several centroids by minimizing the Euclidean distance to the centroids.[47] The algorithm starts by defining the number of clusters (k), which is hyperparameters as demonstrated in Figure 3. The placement of the centroids is initiated at random, and the approach proceeds to divide the data (i.e., observations) based on the shortest distance to the centroids. New locations of other centroids are then inferred based on the average data values within each group. Ultimately, the algorithm runs until there are no changes at the clustering.

2.4 | Probabilistic Naive Bayes algorithm

For multi-classification tasks, the Naive Bayes technique is a well-known supervised machine learning algorithm.[48] As a result of the clustering using K-means, it is utilized in this study to investigate whether to charge or discharge an EV inside a cluster. In particular, it determines the likelihood of EV to charge and stay linked to the utility grid based on studying the historical data of the whole vehicles inside the cluster.[49] The generic form Naive Bayes algorithm is given in Equation (14).

$$P(C_k|x) = \frac{P(x|C_k) \times P(C_k)}{P(x)}, \tag{14}$$

where C_k is the output of class-k, x_k is the dataset attributes $(x_1, x_2, ..., x_n)$, $P(x|C_k)$ is called the likelihood to charge the vehicle, $P(C_k)$ is the prior, $P(x)$ is the evidence, and $P(C_k|x)$ is posterior. The posterior is the target to estimate and fortunately its value is binary, which is relevant to EVs battery status.

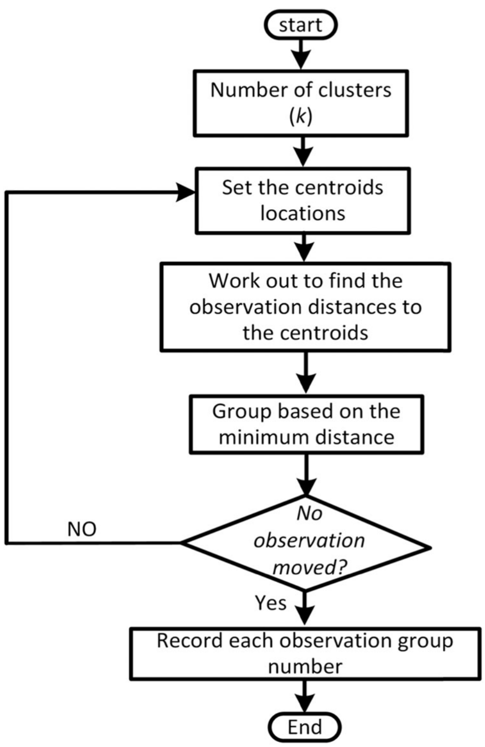

FIGURE 3 K-means clustering concepts.

3 | PROBLEM FORMULATION

The DR with V2G issues comprises an objective function subject to constraints. It is assumed that the V2Gs in DR operate at a unity power factor and whatever output kWh available from them in kWh is directly supplied/absorbed from the grid.

3.1 | Objective function

The proposed optimal scheduling is to minimize the fitness function J, which minimizes the sum of generation, DR, and V2G total operational costs.

$$J = \min\left(\sum_{i=1}^{N_g} C_g^i\left(P_g^i(t)\right) + \sum_{j=1}^{N_d} C_{DR}^j\left(DR^j(t)\right) + \sum_{k=1}^{N_v} C_{V2G}^k\left(V2G^k(t)\right)\right), \tag{15}$$

where N_g, N_d, and N_v are the total number of DGs, DR virtual resources, and V2G units.

3.2 | DR as virtual generating units

In this study, DR is transformed into a virtual generating unit, in which each demand reduction is handled as an equivalent generating resource. The DR price is treated in terms of its marginal cost (mc) as in (16).[1,2]

$$mc^j = \frac{P_H - P_L}{2DR^j(t)} s^j(t) dr^j(t) + P_L s^j(t) = \alpha^j(t) dr^j(t) + \beta_j(t), \tag{16}$$

where P_H and P_L are the high and low electricity prices when customer j shares in the DR program. $dr^j(t)$ represents the hourly DR contribution by customer j. $DR^j(t)$ is the average DR of customer j during its contribution in DR. One can refer to Kwang and colleagues[1,2] for the exact determination of the DR parameters. The DR resources commands are given in Figure 4. The power demand peaks from 8 a.m. to 21 p.m., implying that the costs are passed on to the end-user. The DR pattern is established in such a way that, during the peak hours, the developed optimizers specify the optimal virtual generation or the demand reduction thereby reducing the total costs.

3.3 | On-grid energy storage EVs batteries

V2G energy storage batteries are represented by a parking lot at the relevant bus. When connected to the utility grid, plugin electric vehicles (PEVs) could be a load demand or a resource. Based on the SOC, the parking lot is a large battery, whose capacity is defined by the size of the individual parking vehicle batteries' that are shared in the DR program. This big battery is highly stochastic in terms of the EV number and SOC.[50–53] Furthermore, the number itself depends on the incoming and exiting cars. For this reason, the parking lot battery is simplified by a probability density function (PDF) as will be demonstrated in the next section. The main target is to find the optimal sharing capacity according to the PDF so that the total operational costs are minimized. Accordingly, a near-optimal portion from the big battery at the parking lot is treated as virtual inertia DR.

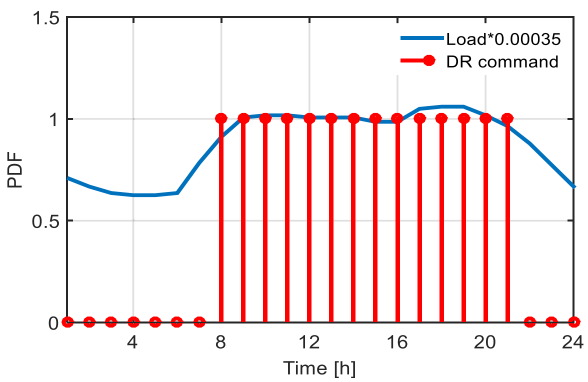

FIGURE 4 Demand response (DR) command pattern.

3.4 | K-means optimal number of clusters

The K-means algorithm is utilized to reduce the distances between points in a cluster. It, on the other hand, aims to maximize the distances between clusters. The goal of the current research is to establish whether the parking lot battery is a load demand or a distributed energy resource. As a result, clusters of centroids with SOC of greater than 50% are considered resources and are likely to be part of the DR program, while the remainder is considered load demands. However, determining the optimal number of clusters is a challenge. The Euclidean distance within cluster is based on the sum of squares, sometimes called inertia. As a result, inertia could be a useful way to choose a cluster number that is close to optimum. Furthermore, the Silhouette score (Si) concept might be utilized to measure the quality of K-means clustering fit.[47] The Si score is calculated for each data point in each cluster based on the following data observation distances:

1- The average distance (a) between a single observation (i.e., data point) and all other data points in a cluster.
2- The average distance (b) between the observation and the next closest cluster's other data points. In turn, the Silhouette score is estimated as:

$$Si = \frac{b - a}{\max(a, b)}, \tag{17}$$

where max refers to selecting the maximum value between a and b. The cluster is adequately split if S is closer to unity. A score approaching zero would indicate overlapping clusters with samples extremely close to the surrounding clusters' border. A negative score of −1 to 0 demonstrates that the data was incorrectly allocated to the clusters.

3.5 | Implementation of Naive Bayes probabilistic

The K-means clustering divides the EVs into clusters according to their SOC. Determining the status of the incoming cars sophisticated task. Since Naive Bayes is a trained-based approach based on the EVs historical data, therefore, it is expected to provide a robust decision of EVs that are likely to be part of the DR program or considered load demands provided that the centroids have the same SOC. The Factors that impact the EVs drivers were investigated before in the literature,[49,54] on the basis of which an excel sheet was established as in

Appendix section. The "OneHotEncoder" technique is employed to convert the Table A2 information into binary data. The accuracy of the naive is estimated according to (18), in which $\hat{y}$ is the predicted value of y and n_{EV} is the net EVs within a cluster.

$$\text{accuracy}\,(y,\hat{y}) = \frac{1}{n_{EV}}\sum_{i=0}^{n_{EV}-1} 1 : if\;\; \hat{y} = y. \tag{18}$$

3.6 | Constraints

The power balance constraints are given in (19) to ensure the electrical load/generation balance at a time interval t, in which N_c represents the total number of customers' loads. The DG, DR resources, and V2G limitation constraints are given in Table A1.

$$\sum_{i=1}^{N_g} P_g^i(t) + \sum_{j=1}^{N_d} DR^j(t) + \sum_{k=1}^{N_v} V2G^k(t) = \sum_{j=1}^{N_c} P_l^j(t) \quad \forall\; t \in T. \tag{19}$$

For a group of transmission branches (N_{br}), the power losses are estimated as (20), in which R_{br} is the branch resistance and I_{br} is the corresponding current.

$$P_{\text{LOSS}}(T) = \sum_{i=1}^{N_{br}} I_{br}^2 R_{br}. \tag{20}$$

For N buses, the voltage and current constraints are given as in (21) and (22), respectively.

$$V_{\min} \le V_i \le V_{\max} \quad \forall\; i \in N \tag{21}$$

$$I_i \le I_{\max} \quad \forall\; i \in N_{br}. \tag{22}$$

For S is the subset of transmission lines branches, which connect bus i and bus k, the next equations are used to estimate the active and reactive powers as:

$$P_j = g_{ik}V_i^2 - V_iV_k(g_{ik}\cos(\theta_i - \theta_k) + b_{ik}\sin(\theta_i - \theta_k)) \quad \forall\; i,k \in S, \tag{23}$$

$$Q_j = b_{ik}V_i^2 - V_iV_k(g_{ik}\cos(\theta_i - \theta_k) + b_{ik}\sin(\theta_i - \theta_k)) \quad \forall\; i,k \in S, \tag{24}$$

where j iteration is the iteration number, g_{ik} is the branch conductance, and b_{ik} is the branch substance. For DGs, the power generation constraints are specified as (25), in which G is the total number of DGs.

$$P_{g,\min}^i \le P_g^i \le P_{g,\max}^i \quad \forall\; i \in G. \tag{25}$$

For customer j, the DR constraints are assumed in (26), in which M_j is the maximum allowable reduction in the DR program. Furthermore, the DR prices limits are given in (27), in which $P_d(t)$ is the energy price at hour t.

$$0 \le DR_j \le M_j, \tag{26}$$

$$P_H \le P_d(t) \le P_L. \tag{27}$$

For a parking lot facility, the DR participation is governed in (26), in which $V2GR$ is the DR participation.

$$0 \le V2GR \le PDF(t) \times V2G_{\max} \tag{28}$$

3.7 | Degree of satisfaction

In this study, an index is defined in (29), which is considered as a measure for the degree of satisfaction of a customer in the DR program. The higher η is the higher the customer's degree of satisfaction.

$$\eta = 1 - \frac{P_a - P_b}{P_b}, \tag{29}$$

where P_a is the total electricity costs after considering DR, and P_b is the total electricity costs before considering DR.

3.8 | DR participation ratio

The customer participation rate represents a customer contribution in the DR program as given in (30), in which M represents the maximum DR magnitude a customer j can allow. It depends on the customer performance.

$$PR^j(t) = \frac{DR^j(t)}{M^j(t)} \quad \forall\; t \in T. \tag{30}$$

3.9 | Implementation of self-adjusted PSO

Optimal operation of generation and DR resources with V2G offers a way to decrease total operational costs. Figure 5A shows a flow chart of the developed probabilistic SAPSO algorithms. Herein, the developed SAPSO algorithms are developed to manage the optimal day-ahead scheduling of generation, demand resources, and the V2G PDF operation. To verify the economical viewpoint, it is required to run load flow analysis.

The algorithms start by defining the hyperparameters and then generate a PDF for the V2G possible scenarios.

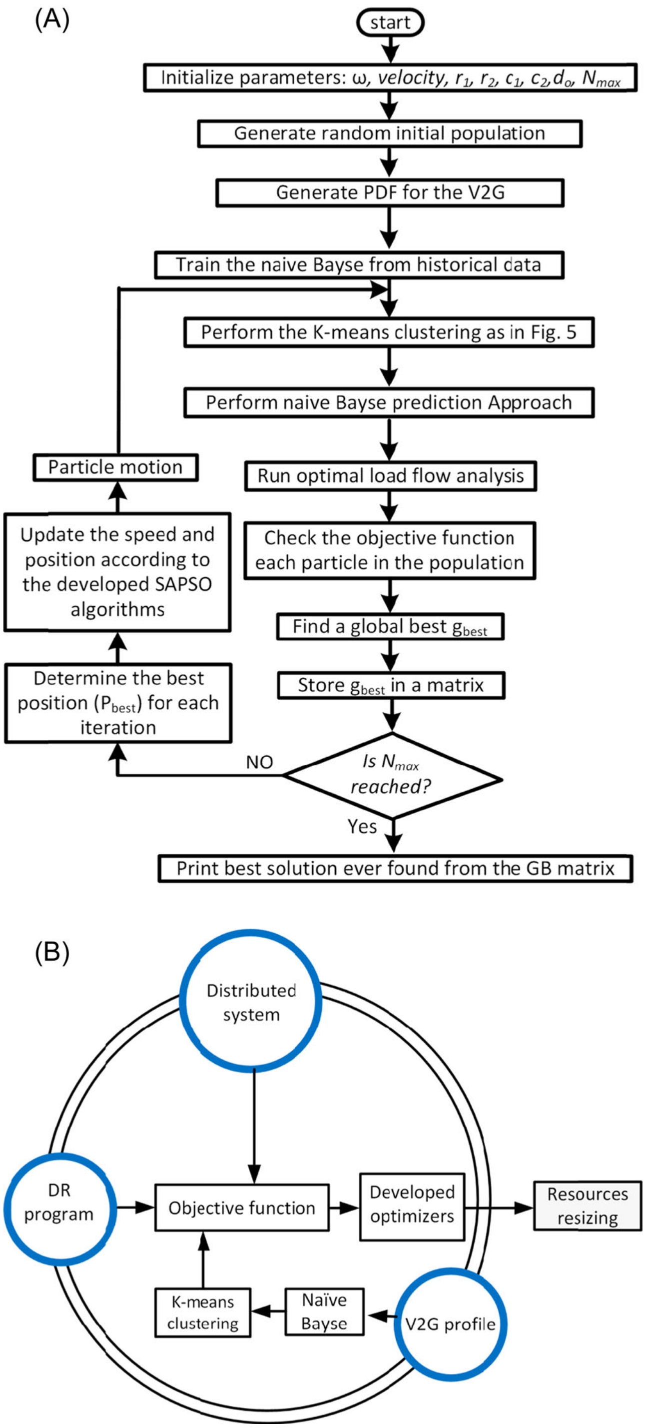

FIGURE 5 Mathematical formulation description. (A) Probabilistic modified particle swarm optimization-based day-ahead optimization; and (B) overview of the mathematical formulation. DR, demand response; V2G, vehicle to grid.

Provided that each cluster has the same SOC centroid, the Naive Bayes classifier is trained. The training factors include battery SOC, driver yearly income, education level, wind speed, and the main goal is to determine the driver's proclivity to charge the battery. To cover the EVs' is trained for each cluster, uncertainty, the K-means clustering demonstrated in Figure 3 is checked to identify the electric cars that would engage in the DR program. In each cluster, the Naive Bayes classifier is used to predict whether the EVs will charge or discharge. The algorithms then proceed to find a global best solution that reduces overall costs while meeting the objective function adequately. Eventually, the optimal solution is identified throughout the predetermined number of iterations. The problem formulation is to put forward the near-optimal solution for the distributed system in terms of the economic issues as demonstrated in Figure 5B. The fundamental concept is to transform such a stochastic problem into a deterministic concept. To forecast EV charge/discharge status, the Naïve Bayes algorithm is employed. The SOC is thus produced at random. To find the essential clusters, K-means clustering is used. To meet the objective function, deterministic optimizers search for the best or nearly best decision variables involoved in (15). The remaining issues are related to the DGs; however, they are deterministic in their nature. Following the activation of the hyper-parameters, each of the deterministic optimizers seeks to minimize the objective function provided in (15), which contains the decision variables. The decision variables comprise the size of the DGs and DR participation as well as the parking lot battery. In turn, both the day-ahead total expenses, the load, and the resources are scheduled in a manner to increase the customer's degree of satisfaction.

4 | SIMULATED RESULTS

For optimal network functioning in distributed systems, DGs and utility-owned V2G aggregators have to be efficiently rescaled. To develop the day-ahead sizing strategy of energy storage systems of EVs parking lots and DGs in smart distribution systems, compliant DR, which is regarded as an advanced step towards a smart grid, is used as a result of their penetration into the power systems. Applying the developed problem formulation algorithm in the previous section to the modified IEEE 24 RTS bus network will help find the near-optimal times to schedule DG generating units, DR, and V2G resources in accordance with the objective function in (15). Metaheuristics are useful methods for finding the near-optimal size within the scheduling problem, which would both assist to lower total expenses and provide an acceptable degree of satisfaction. Thus, the obtained results are compared with two algorithms, namely the mature GA and the traditional exploitive PSO, to demonstrate the efficacy of the two developed SAPSO optimizers and address the aforementioned constraints. In the day-ahead scheduling, the EVs' states at the parking lots are adjusted in the DR program utilizing both the developed K-means clustering and the Naïve Bayes probabilistic techniques. The GA, PSO, SAPSO#1, and SAPSO#2 models are constructed using Matlab 2017a with a 1-h time step. Python is used to investigate the Naïve Bayes classifier and K-means clustering. The Appendix section includes the developed SAPSO#1 and SAPSO#2's parameters.

The following investigation scenarios attempt to reduce total operating expenses by including day-ahead scheduling with an acceptable level of satisfaction. Initially, the case study is presented followed by investigation of the effectiveness of the developed optimizers. Overall, the decision variables are the DGs, DR resources, and parking lots sizing in kW. Applying the four optimizers results in a reduction of overall costs with an acceptable degree of satisfaction, scheduling both DGs and V2G cars, and comparing the execution times of the individual optimizers. The single optimizers' hourly energy production shares are demonstrated to provide a fair comparison. Pseudocode 1 illustrates the general approach to determine the DGs, DR, and V2G status depending on the load profile and energy costs. However, the charging or discharging mode of the EVs is determined by K-means clustering and the Naive Bayes techniques. In addition, deterministic optimizers are used to estimate the objective function. In turn, they are then given the results of the charging and discharging modes, and they go on to obtain the sizing decision of the variables in accordance with the varied profitability prices.

4.1 | Case study

Figure 6 shows a modified one-line diagram of the IEEE 24 reliability test system. It consists of 11 generation units at Buses 2, 1, 7, 13, 14, 15, 16, 18, 21, 22, 23. Bus#13 is considered the slack bus. The DR buses are located at 3, 4, 5, 8, 9, 10, 19, and 20. Among the DR buses, V2G charging stations are assumed at Buses 3 and 19 as shown in Figure 6 with red circles. The developed DR scheduling has been applied to the IEEE 24-bus RTS bus network. The electrical demand for a day-ahead is given in Figure 7 where the maximum loading is 2650.5 MW and peaks at Hour 18. The locations of the DGs, DR resources, and V2G resources are given in Figure 6.

4.2 | Effectiveness of the developed algorithms

Figure 8 demonstrates a convergence behavior test of the objective function for the developed optimizers. GA illustrates a longer time to relax. Meanwhile, other developed algorithms show satisfactory performance. Yet, it is obvious that the developed SAPSO#1 is a strong competitor to the other algorithms. It converges fast towards the near-optimal point.

Each optimizer tries to identify the best amount of DR at a specific time in response to DR command signals. The size of the demand profile before and after the DR program remains unchanged, but the DR reaction adjusts the flexible load timespan, resulting in a more cost-effective solution.

Pseudocode 1: Mathematical formulation strategy

Inputs: load profile, energy prices, distributed system parameters, cars historical data
Initialization: the deterministic optimizers
$J \leftarrow \mathrm{f}(\mathrm{costs}, Power)$
$PDF(t) \leftarrow f(t)$
Train the Naïve Bayes algorithm
    for $t \coloneqq 1$ to N_{max}
        Run the K-means clustering
        Run Naïve Bayes prediction approach
            if $\sum_{t=1}^{N} SOC \geq 0.5$
                charge mode
            else
                discharge mode
            end if
        estimate J
    end for

$$\left.\begin{cases} costs \leftarrow f(DGs, DR, V2G) \\ Degree\ of\ satisfaction \leftarrow f(costs) \\ load\ shifting \end{cases}\right\} Problem\ formulation$$

Outputs: Size of day-ahead DR, DGs, and the parking lot

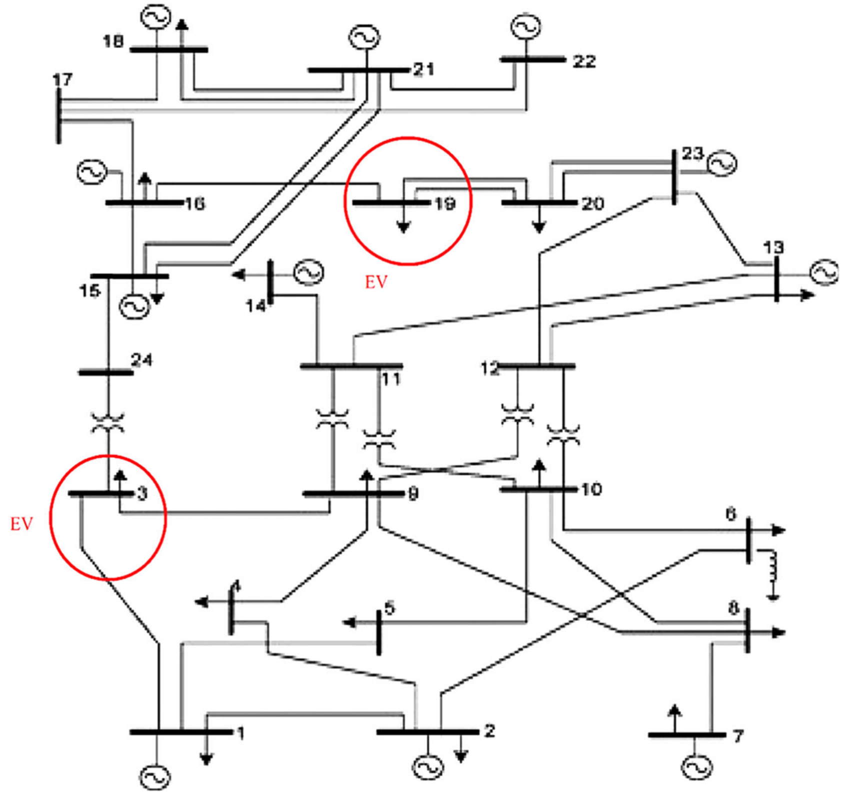

FIGURE 6 Modified IEEE 24 reliability test system.

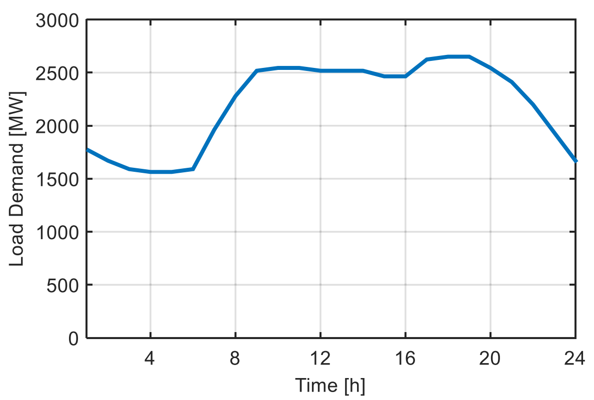

FIGURE 7 Typical system hourly demand profile.

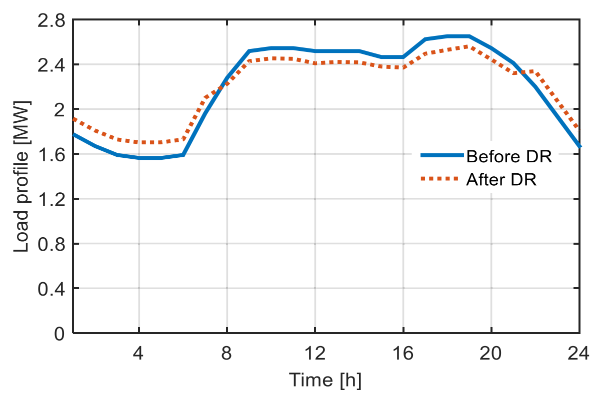

FIGURE 9 Demand profile before and after demand response (DR) program via SAPSO#1.

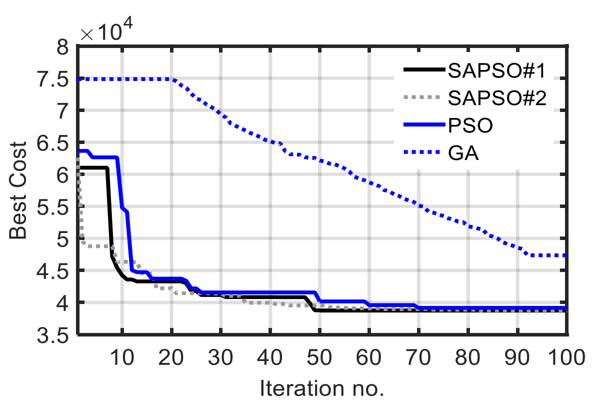

FIGURE 8 Objective function variation. GA, genetic algorithm; PSO, particle swarm optimization.

The load profile before and after the DR program via SAPSO#1 is demonstrated in Figure 9, in which the algorithm moves the load during peak hours into low demand requirements times. Furthermore, the total costs of the developed algorithms are shown in Figure 10.

The developed optimizers are based on the PSO, which has a robust exploitation feature. Besides, the major target of this section is to verify the effectiveness of the developed optimizers compared to the GA and the exploitive PSO. Accordingly, the developed PSO-based optimizers are expected to demonstrate a satisfactory exploitation feature to meet the objective function, which is verified in Figure 8

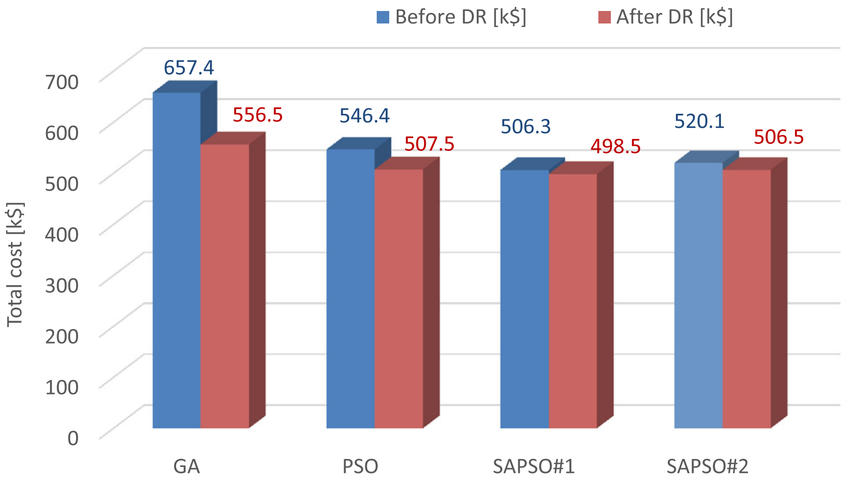

FIGURE 10 Total costs before and after considering the demand response (DR) program.

TABLE 1 Comparison results of the individual optimizers.

Algorithm	Maximum voltage (pu)	Minimum voltage (pu)	Degree of satisfaction	Time of simulation (s)	No. of iterations
GA	1.0000	0.9336	0.7021	92	100
PSO	1.0000	0.9337	0.9211	86	100
SAPSO#1	1.0000	0.9335	1.0157	89	100
SAPSO#2	1.0000	0.9336	0.9731	85	100

Abbreviations: GA, genetic algorithm; PSO, particle swarm optimization.

and Table 1, respectively. Nonetheless, both the total cost reduction and the execution time are considered in the current study to judge which optimizer is more effective. The comparison cost reduction results are given in Table 1. SAPSO#1 shows a reduction of $7.8k (i.e., 506.3–498.5), which represents a reduction of 1.65% with respect to the "*After the DR*" case. Meanwhile, SAPSO#2 shows a cost decrease of $13.6k (2.7%), which represents 29.8% when compared to the GA considering the "*before the DR*" example. Consequently, the lowest day-ahead costs are provided by SAPSO#1, which represents 24% compared to the GA considering the "*before the DR*" case. In addition, it offers the greatest degree of satisfaction. However, the shortest time of the simulation is provided by SAPSO#2. It records 85s with a PC having an Intel Core i5-7200U CPU 2.5 GHz.

4.3 | Optimal PEV charging with DR

The main target of optimally scheduling the PEVs to the utility grid is to determine the optimal charging profile and the corresponding daily benefit cost, which comes back to the customer through the participation in the DR issue according to Section 3 and the constraints in Table A1. With the assumption that the parking lot is a large battery, a PDF with a bell-shaped curve for V2G is assumed for the battery SOC as in Figure 11.

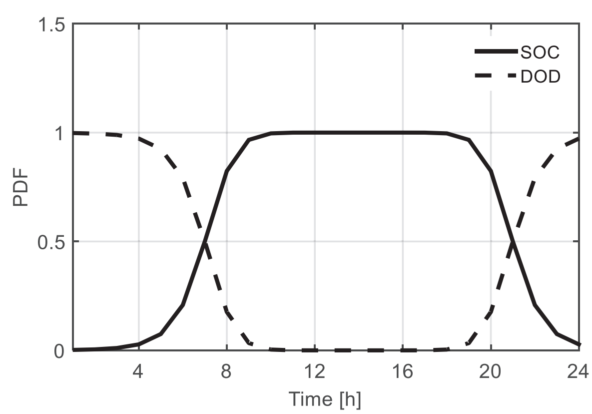

FIGURE 11 Parking lot battery state of charge (SOC).

The scheduling method in the current study is utilized in the distributed systems primarily to focus on the electric automobile operations in which the EVs battery status is the point of interest. The main purpose is to minimize the total energy costs. On the other hand, the PSO-based techniques in the current study are dependent on training to identify the V2G state, which is based on the charging and discharging rates of the EVs that fluctuate arbitrarily over time. For this reason, Naive Bayes is trained randomly as in Table A2 shown in the Appendix section. Thus, to consider the uncertainty within the parking lot battery hourly status, a ±20% variability around each SOC observation of the PDF is assumed as shown in Figure 12A. The parking lot battery is assumed to be a big virtual battery. Since it is virtual, the parking lot battery is therefore made simpler by a PDF. The number of vehicles entering and exiting the parking lots, which essentially meets the V2G typical operating SOC requirements, influences this virtual battery capacity. Ultimately, the individual automobiles operate realistically (between 20% and 95%), but the virtual battery capacity is dependent on the incoming and departing vehicles. Herein, the goal is to determine whether the parking lot is a load demand or is considered a distributed energy resource. The investigation of the Silhouette score and the inertia in Figure 12B,C, respectively, illustrate that the Silhouette score decreases fairly from 0.54 to approximately 0.4 at 9 clusters. Since the inertia curve has an elbow shape, it might help figure out how many clusters are satisfactory. Fortunately, the investigation reveals that 10 clusters slightly alter the inertia curve compared to 9 clusters; therefore, 9 clusters are chosen in this study.

Figure 13 depicts the near-optimal clusters, with each centroid represented by the symbol ×. The Naive Bayes classifier is used to predict the status of an EV battery either to charge or discharge according to pretrained historical data as in Appendix section. In their participation in the DR program, the drivers with "YES" admit selling energy to the utility grid, and the others are considered as hourly loads. The battery SOC range is divided into three main statuses: low, medium, and high. Such statuses are converted to zeros and ones using the "OneHotEncoder" technique accessible in Python packages. Likewise, additional factors that influence the battery charging are transformed into binary statuses. With the Gaussian fitting option, Naive Bayes prediction achieves an accuracy of 80%. Assuming the EVs' battery capacity is in the range of 50 kWh and assuming 1000 total number of EVs at the relevant buses, the aggregation of the predicted only cars might sell energy to the utility grid according to the PDF perspective. Other cars are considered as load demands. Based on the SOC, Figure 14 shows the optimal charging profile of V2G at Bus#3. The hourly benefit-cost for Buses#3 and #19 are given in Figures 15 and 16, respectively. Based on the training data in Table A2, the near-optimal V2G charging is demonstrated in Figure 14 at Bus#3 wherein a parking lot exists. The act of charging indicates that the owners of EVs pay money to acquire electricity from the grid. However, Figures 15 and 16 show how the V2G may contribute to the DR program at different times, which lowers the total

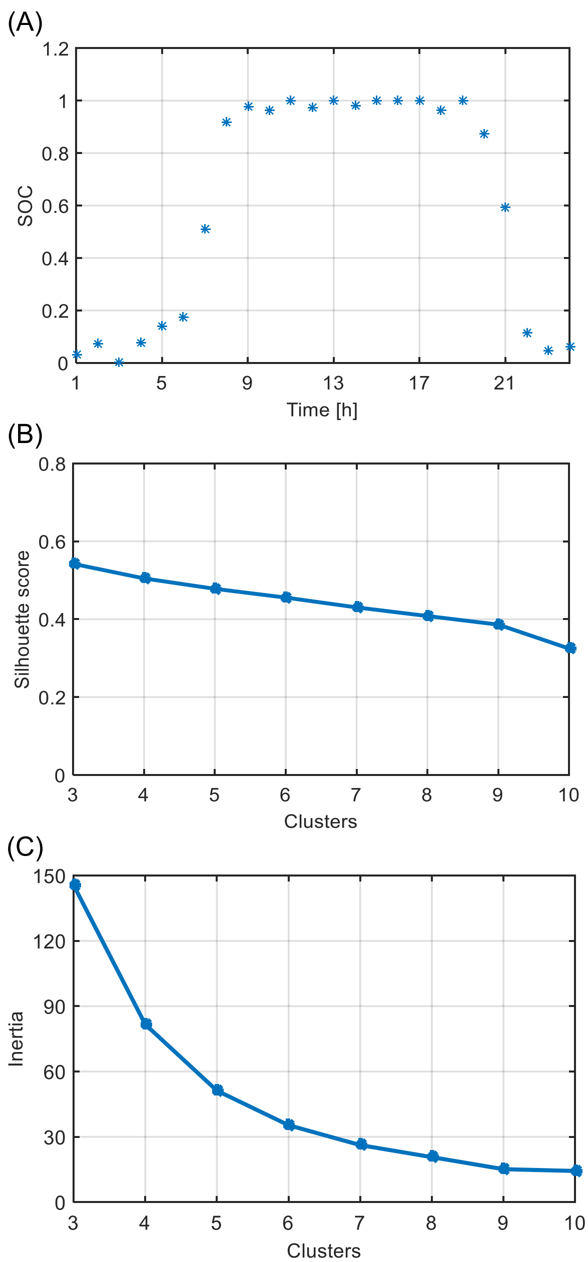

FIGURE 12 K-means indices; (A) parking lot variability, (B) Silhouette score, and (C) inertia.

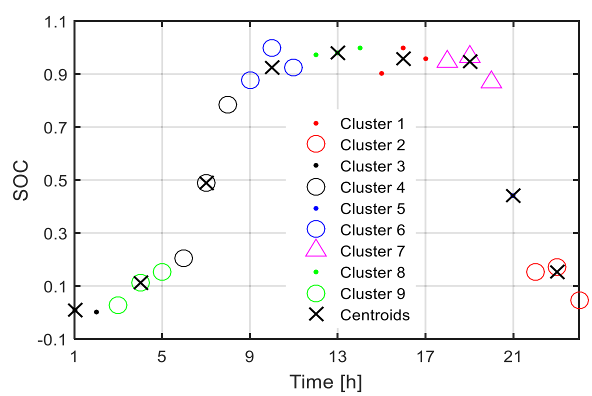

FIGURE 13 Near-optimal vehicle to grid clustering.

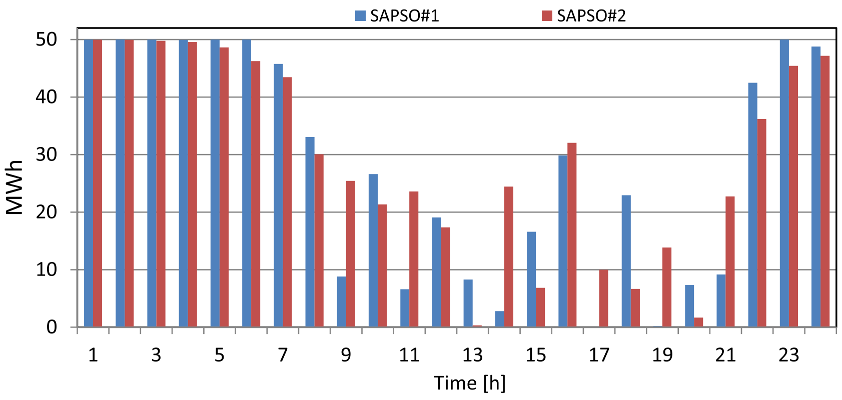

FIGURE 14 Optimal vehicle to grid charging at Bus#3.

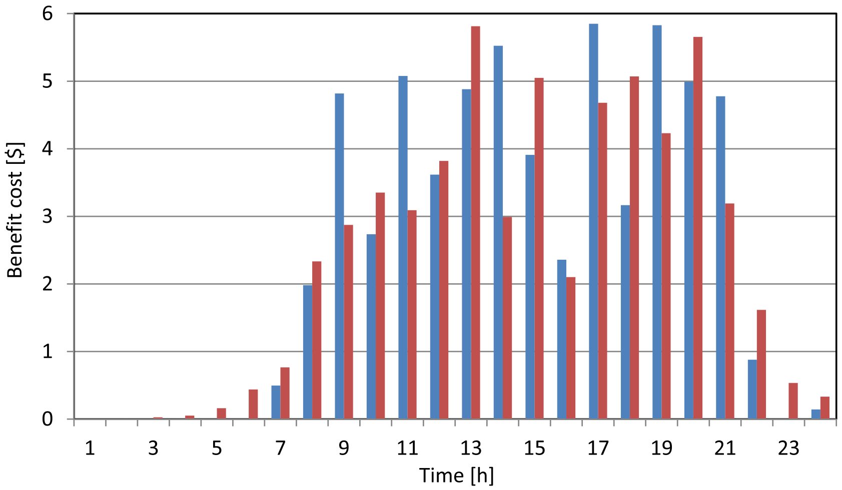

FIGURE 15 Benefit-cost of vehicle to grid charging at Bus#3 (blue: SAPSO#1, red: SAPSO#2).

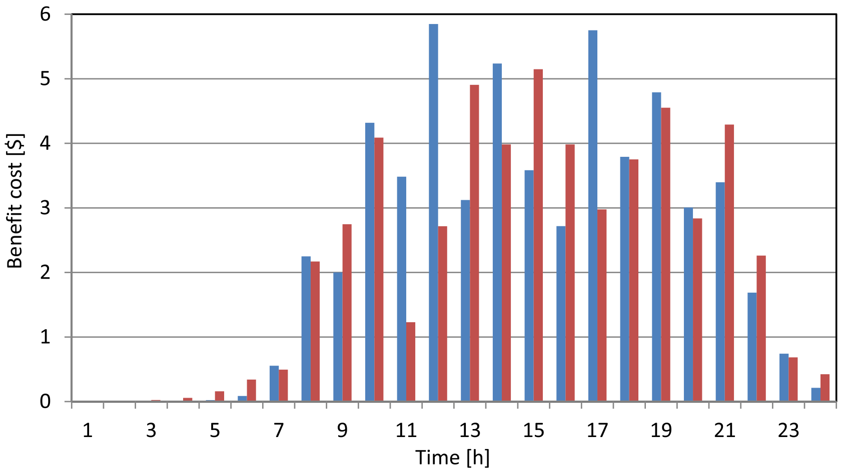

FIGURE 16 Benefit-cost of vehicle to grid charging at Bus#19 (blue: SAPSO#1, red: SAPSO#2).

expenses by the amounts therein shown. Summing such day-ahead benefit costs is shown in Table 2, which are saved from the customers' side. The findings show that SAPSO#1 and SAPSO#2 both save around \$117.7 (e.g., \$61.05 + \$56.62) and \$112, respectively. In turn, SAPSO#1 exhibits revenue improvement compared to SAPSO#2 by 5%, referred to the latter results. It is clear that SAPSO#1 certainly strengthens the customer benefit cost over SAPSO#2.

4.4 | Impact of scheduling DR and V2G resources upon running cost

Figures 17–19 show the system performances involving DR and V2G resources via SAPSO#1 from 8 to 21 h. Once, the DR signal is received, the algorithm seeks the optimal DR value to minimize the total costs. It can be observed that the demand resources decrease the overall running costs. The optimal scheduling enables demand

TABLE 2 Net daily benefit-cost of V2G.

	Daily benefit-cost ($)	
Algorithms	**Bus#3**	**Bus#19**
SAPSO#1	61.05189	56.62496
SAPSO#2	58.18773	53.84188

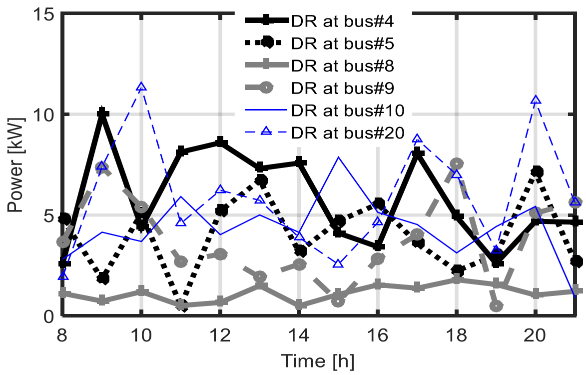

FIGURE 17 Demand response (DR) resources scheduling with SAPSO#1.

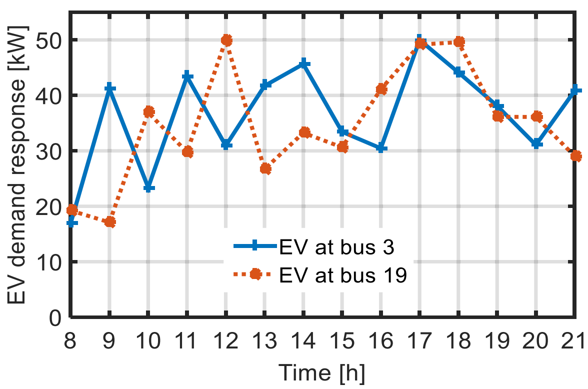

FIGURE 18 Vehicle to grid resources scheduling with SAPSO#1. EV, electric vehicle.

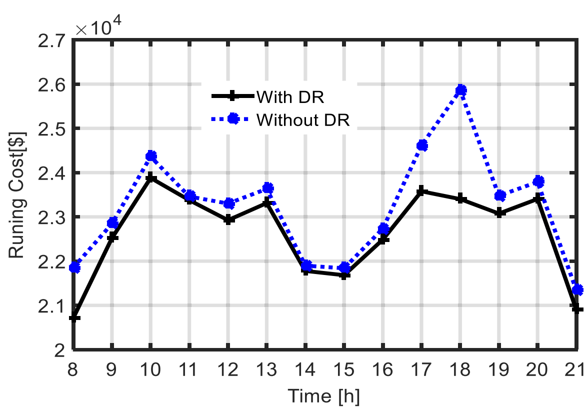

FIGURE 19 Running cost with demand response (DR).

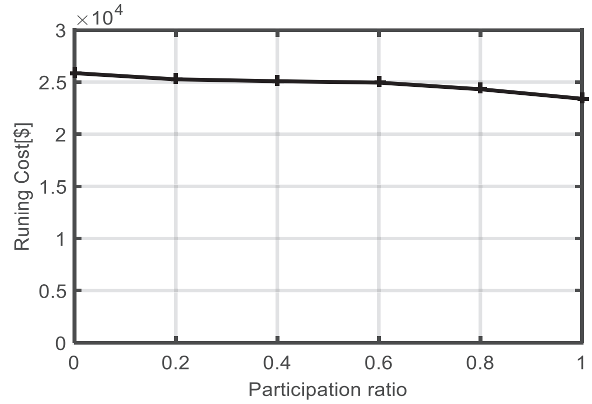

FIGURE 20 Running cost versus participation rate at Hour 18.

resources to become competitive to the DGs with the highest costs. Thus, the effectiveness of the developed SAPSO is verified.

4.5 | Impact of DR participation ratio

The customer participation rate represents a customer contribution to the DR program as given in Equation (30). Figure 20 shows the echelon of the daily running costs versus a customer participation rate via SAPSO#1 at Hour 18, which meets the maximum loading conditions. Below (PR = 0.5), DR has a slight impact on the running costs. It could be concluded that the above PR equals 0.5, and the DR scheduling could improve the net hourly cost.

5 | DISCUSSION

Table 3 compares the outcomes obtained by a few schedulers that produced adequate performance in the literature. In each study, a fundamental situation is taken into account, from which the data in the second column was derived. Despite the fact that the figures in Table 3 vary based on the current energy prices, the characteristics of the distributed systems under consideration, or at the level of microgrids, RESs, and DGs, it is clear that the developed optimizer performs satisfactorily. Yet, the findings in Table 3 show that to achieve greater cost savings, a more sophisticated stochastic approach, such as reinforcement learning, is required. From the above case studies, the following notices can be drawn:

1- Both of the developed controllers show better performance compared with GA and the conventional PSO.
2- SAPSO#2 outperforms the other algorithms in terms of the time consumed for optimal scheduling processing.

TABLE 3 Optimizers, effectiveness.

Method	Cost saving (%)
Greedy[55]	85
GA[56]	5.9
Mixed integer linear programming[57]	29
Markov chain[29]	24
First in first Saving[58]	3.4
SAPSO#1	24
SAPSO#2	29.8

Abbreviation: GA, genetic algorithm.

3- SAPSO#1 has the highest degree in terms of convergence processing.
4- Optimal scheduling of DR and PEV resources enables them to be competitors to DGs with the operational highest costs.

6 | CONCLUSION

The day-ahead sizing of the flexible distributed generators and resilient EV aggregators in distributed networks is investigated in this study. Besides, two modified probabilistic SAPSO algorithms integrated K-means clustering, and Naive Bayes classifiers were utilized to evaluate the optimal day-ahead scheduling of generation and remand response with V2G participation. The optimal scheduling was conducted to minimize the total operational costs of generations, DR, and V2G resources. The results show that the running costs decrease as the customer participation rate increases. The K-means clustering technique was utilized to divide the EVs into clusters according to their batteries' state of arrival. The Naive Bayes classifier was employed to predict the EVs which participate in the day-ahead scheduling. From the above development and discussions, the next conclusions could be drawn: (1) the developed algorithms allow the optimal scheduling of generation and remand response with V2G participation in an economic manner. (2) The effectiveness of the developed SAPSO#1 to minimize the total running costs was achieved and compared with other algorithms. (3) The algorithm is effective and can be cooperated with optimal scheduling issues with different operating conditions to minimize total operating costs and maximize net savings.

For the purpose of future work, this study could be extended within resilient interconnected microgrids with more advanced machine learning techniques such as reinforced machine learning-based algorithms. A future study might also look at the impact of façade thermal photovoltaic systems for storing green hydrogen and the versatile V2G energy storage batteries.

ACKNOWLEDGMENT

This study was supported by the Department of Electrical Engineering and Automation, School of Electrical Engineering, Aalto University, Espoo, Finland.

ORCID

Farag K. Abo-Elyousr https://orcid.org/0000-0002-1692-5003
Adel M. Sharaf https://orcid.org/0000-0002-4147-0901
Mohamed M. F. Darwish http://orcid.org/0000-0001-9782-8813
Matti Lehtonen https://orcid.org/0000-0002-9979-7333
Karar Mahmoud http://orcid.org/0000-0002-6729-6809

REFERENCES

1. Kwang HG, Kim J. Optimal combined scheduling of generation and demand resource constraints. *Appl Energy*. 2012;96:161-170.
2. Alazemi FZ, Hatata AY. Ant lion optimizer for optimum economic dispatch considering demand response as a visual power plant. *Electr Power Compon Syst*. 2019;47:629-643.
3. Jalili H, Siano P. Modeling of unforced demand response programs. *Int J Emerg Electr Power Syst*. 2021;22:233-241.
4. Sharifi R, Fathi SH, Moghaddam A, Guerrero JM, Vahidinasab V. An economic customer-oriented demand response model in electricity market. Paper presented at: International Conference on Industrial Technology (ICIT), IEEE conference; 2018:1149-1153.
5. Bie Z, Xie H, Hu G, Li G. Optimal scheduling of power systems considering demand response. *J Mod Power Syst Clean Energy*. 2016;4(2):180-187.
6. Zheng W, Wu W, Zhang B, Lin C. Distributed optimal residential demand response considering constraints of unbalanced distribution networks. *IET Gener Transm Distr*. 2018;12(9):1970-1979.
7. Aalami HA, Moghaddam P, Yousefi GR. Modeling and prioritizing demand response programs in power markets. *Electr Power Syst Res*. 2010;80:426-435.
8. Campos J, Csontos C, Harmat A, Csüllög G, Munkácsy B. Heat consumption scenarios in the rural residential sector: the potential of heat pump-based demand-side management for sustainable heating. *Energy Sustain Soc*. 2020;10:40.
9. Chau S, Kirschen D. Quantifying the effect of demand response on electricity markets. *IEEE Trans Power Syst*. 2009;24:1199-1207.
10. Shayesteh E, Elias M, Kohan N, Moghaddam MP. Security-based demand response allocation. Paper presented at: IEEE Power & Energy Society General Meeting. 2009.
11. Shareef H, Maytham SA, Mohammad A, Al-Hassan E. Review on home energy management system considering demand response, smart technologies, and intelligent controllers. *IEEE Access*. 2018;6:24498-24509.
12. Muller T, Most D. Demand response potentials: available when needed? *Energy Policy*. 2018;115:181-198.

13. Asadinejad A, Rahimpour A, Tomsovic K, Qi H, Chen C. Evaluation of residential customer elasticity for incentive based demand response. *Electric Power Syst Res*. 2018;158:26-36.
14. Srivastava A, Passal SV, Laes E. Assessing the success of electricity demand response programs: a meta-a meta-analysis. *Energy Res Soc Sci*. 2018;40:110-117.
15. Nan S, Zhou M. Optimal residential community demand response scheduling in smart grid. *Appl Energy*. 2018;210: 1280-1289.
16. Viana MS, Junior GM, Udaeta MEM. Analysis of demand response and photovoltaic distributed generation as resources for power utility planning. *Appl Energy*. 2018;217:456-466.
17. Huo D, Gu C, Yang G, Le. Blond S. Combined domestic demand response and energy hub optimization with renewable generation uncertainty. *Energy Procedia*. 2017;142:1985-1990.
18. Basu M. Fast convergence evolutionary programming for multi-area economic dispatch. *Electr Power Compon Syst*. 2017;45:1629-1637.
19. Elnozahy A, Ramadan HS, Abo-Elyousr FK. Efficient metaheuristic Utopia-based multi-objective solutions of optimal battery-mix storage for microgrids. *J Clean Prod*. 2021;303:127038.
20. Goudarzi S, Hassan W, Anisi MH, et al. ABC-PSO for vertical handover in heterogeneous wireless networks. *Neurocomputing*. 2017;256:63-81.
21. Ghorbani N, Kasaeian A, Toopshekan A, Bahrami L, Maghami A. Optimizing of a hybrid wind-PV-Battery system using GA-PSO and MOPSO for reducing cost and increasing reliability. *Energy*. 2018;154:581-591.
22. Sharaf AM, El-Gammal AAA. An optimal voltage and energy utilization for a stand-alone wind energy conversion scheme wecs based on particle swarm optimization PSO. *Int J Power Eng Green Technol*. 2010;1:51-64.
23. Sharaf AM, El-Gammal AAA. A novel error driven dynamic tri-loop controller based on multistage particle swarm optimization-MSPSO for industrial PMDC motor drives. Paper presented at: 6th International Conference-Workshop Compatibility and Power Electronics; 2009.
24. Sharaf AM, El-Gammal AAA. Particle swarm optimization PSO: a new tool in power system and electro technology. In: Panigrahi BK, Abraham A, Das S, eds. *Computational Intelligence in Power Engineering*. Vol 302. Springer-Verlag; 2010:235-294.
25. Kerdphol T, Qudaih Y, Mitani M. Optimum battery energy storage system using PSO considering dynamic demand response for microgrids. *Int J Electr Power Energy Syst*. 2016;83:58-66.
26. Hashemi S, Aghamohammadi MR, Sangrody H. Restoring desired voltage stability security margin based on demand response using load-to source impedance ratio index and PSO. *Int J Electr Power Energy Syst*. 2018;67:143-151.
27. Gough R, Dickerson C, Rowley P, Walsh C. Vehicle-to-grid feasibly: a techno-economic analysis of EV-based energy storage. *Appl Energy*. 2017;192:12-23.
28. Hoehne CG, Chester MV. Optimizing plug-in electric vehicle and vehicle-to-grid charge scheduling to minimize carbon emissions. *Energy*. 2016;115:646-657.
29. Mortaz E, Valenzuela J. Microgrid energy scheduling using storage from electric vehicles. *Electr Power Syst Res*. 2017;143: 554-562.
30. Emara D, Ezzat M, Abdelaziz AY, Mahmoud K, Lehtonen M, Darwish MMF. Novel control strategy for enhancing microgrid operation connected to photovoltaic generation and energy storage systems. *Electronics*. 2021;10(11):1261-1278.
31. Abubakr H, Guerrero JM, Vasquez JC, et al. Adaptive LFC incorporating modified virtual rotor to regulate frequency and tie-line power flow in multi-area microgrids. *IEEE Access*. 2022;10:33248-33268.
32. Elsisi M, Mahmoud K, Lehtonen M, Darwish MMF. Effective nonlinear model predictive control scheme tuned by improved NN for robotic manipulators. *IEEE Access*. 2021;9:64278-64290.
33. Abubakr H, Vasquez JC, Mahmoud K, Darwish MMF, Guerrero JM. Robust PID-PSS Design for Stability Improvement of Grid-Tied Hydro Turbine Generator. Paper presented at: 22nd International Middle East Power Systems Conference; 2021:607-612.
34. Ali MN, Soliman M, Mahmoud K, Guerrero JM, Lehtonen M, Darwish MMF. Resilient design of robust multi-objectives PID controllers for automatic voltage regulators: D-decomposition approach. *IEEE Access*. 2021;9:106589-106605.
35. Mkahl R, Nait-sidi-Moh A, Gaber J, Wack M. An optimal solution for charging management of electric vehicles. *Electr Power Syst Res*. 2017;146:177-188.
36. Bin-Humayd AS, Bhattacharya K. Distribution system planning to accommodate distributed energy resources and PEVs. *Electr Power Syst Res*. 2017;145:1-11.
37. Faddel S, AL-Awami AT, Abido MA. Fuzzy optimization for the operation of electric vehicle parking lots. *Electr Power Syst Res*. 2017;145:166-174.
38. Sadat H. *Power System Analysis*. 2nd ed. McGraw Hill; 2004.
39. Abbas AS, El-Sehiemy RA, Abou El-Ela A, et al. Optimal harmonic mitigation in distribution systems with inverter based distributed generation. *Appl Sci*. 2021;11(2):774-790.
40. Ali ES, El-Sehiemy RA, Abou El-Ela AA, Mahmoud K, Lehtonen M, Darwish MMF. An effective Bi-Stage method for renewable energy sources integration into unbalanced distribution systems considering uncertainty. *Processes*. 2021;9(3): 471-486.
41. Ordoudis C, Pinson P, Morales G, Juan M, Zugno M. *An Updated Version of the IEEE RTS 24-Bus System for Electricity Market and Power System Operation Studies*. Technical University of Denmark; 2017.
42. Yustaa JM, Khodrb HM, Urdanet AJ. Optimal pricing of default customers in electrical distribution system: effect behavior performance of demand response models. *Electr Power Syst Res*. 2007;77:4468-4558.
43. Average retail price of electricity to ultimate customers by end-use sector. https://www.eia.gov/electricity/monthly/epm_table_grapher.php?t=epmt_5_6_a
44. Kennedy J, Eberhart RC. Particle swarm optimization. Paper presented at: Proceedings of IEEE International Conference on Neural Networks; 1995:1942-1948.
45. Chatterjee A, Siarry P. Nonlinear inertia weight variation for dynamic adaptation in particle swarm optimization. *Comput Oper Res*. 2006;33:859-871.
46. Sharaf AM, Mavalizadeh H, Ahmadi A, Shayanfar H, Gandoman FH, Homaee O. Chapter 3 Application of new fast, efficient-self adjusting PSO-search algorithms in power systems' studies. *Classical and Recent Aspects of Power System Optimization*. 1st ed. Academic Press; 2018:33-61.

47. Shahapure KR, Nicholas C. Cluster quality analysis using silhouette score. Paper presented at: IEEE 7th International Conference on Data Science and Advanced Analytics (DSAA); 2020:747-748.
48. Yudhana A, Sulistyo D, Mufandi I. GIS-based and Naïve Bayes for nitrogen soil mapping in Lendah, Indonesia. *Sens Bio-Sens Res*. 2021;33:100435.
49. van Heuveln K, Ghotge R, Annema JA, van Bergen E, van Wee B, Pesch U. Factors influencing consumer acceptance of vehicle-to-grid by electric vehicle drivers in the Netherlands. *Travel Behav Soc*. 2021;24:34-45.
50. Al-Gabalawy M, Mahmoud K, Darwish MMF, Dawson JA, Lehtonen M, Hosny NS. Reliable and robust observer for simultaneously estimating state-of-charge and state-of-health of $LiFePO_4$ batteries. *Appl Sci*. 2021;11(8):3609-3630.
51. Zhou S, Han Y, Yang P, et al. An optimal network constraint-based joint expansion planning model for modern distribution networks with multi-types intermittent RERs. *Renew Energy*. 2022;194:137-151.
52. Prashant □, Sarwar M, Siddiqui AS, Ghoneim SSM, Mahmoud K, Darwish MMF. Effective transmission congestion management via optimal DG capacity using hybrid swarm optimization for contemporary power system operations. *IEEE Access*. 2022;10:71091-71106.
53. Abubakr H, Vasquez JC, Mahmoud K, Darwish MMF, Guerrero JM. Comprehensive review on renewable energy sources in Egypt—current status grid codes and future vision. *IEEE Access*. 2022;10:4081-4101.
54. Wu H, Niu D. Study on influence factors of electric vehicles charging station location based on ISM and FMICMAC. *Sustainability*. 2017;9(4):484.
55. Abdel-Hakim AE, Abo-Elyousr FK. Heuristic greedy scheduling of electric vehicles in vehicle-to-grid microgrid owned aggregators. *Sensors*. 2022;22(6):2408.
56. Moradijoz M, Moghaddam MP, Haghifam MR, Alishahi E. A multi-objective optimization problem for allocating parking lots in a distribution network. *Int J Electr Power Energy Syst*. 2013;46:115-122.
57. Mortaz E. Portfolio diversification for an intermediary energy storage merchant. *IEEE Trans Sustain Energy*. 2020;11(3):1539-1547.
58. Fernandez GS, Krishnasamy V, Kuppusamy S, et al. Optimal dynamic scheduling of electric vehicles in a parking lot using particle swarm optimization and shuffled frog leaping algorithm. *Energies*. 2020;13:6384.

How to cite this article: Abo-Elyousr FK, Sharaf AM, Darwish MMF, Lehtonen M, Mahmoud K. Optimal scheduling of DG and EV parking lots simultaneously with demand response based on self-adjusted PSO and K-means clustering. *Energy Sci Eng*. 2022;1-19. doi:10.1002/ese3.1264

APPENDIX A

1- The relevant parameters for generating, DR, and V2G aggregation units are given in Table A1.[1,2]
2- SAPSO#1 parameters: inertia weight $(W_0) = 0.2$, population = 100, $c_1 = 7.5$, $c_2 = 7.5$, $d_0 = 0.7$, inertia weight damping ratio = 1, and no. of iterations $(N_{max}) = 100$.
3- SAPSO#2 parameters: inertia weight $(W_0) = 0.4$, population = 100, $c_1 = 1.5$, $c_2 = 1.5$, inertia weight damping ratio = 0.99, and no. of iterations $(N_{max}) = 100$.
4- The bell-shaped probability density function, which is a Matlab-based function, and the following parameters are used: $a = 7$, $b = 5$, $c = 14$.
5- The following Table A2 gives the historical data of EVs within clusters. It should be noted that this table is created randomly.

TABLE A1 Generating, DR, V2G units characteristics.

Unit type	Bus no.	α^i	β^i	γ^i	STC^i	P_{min} (MW)	P_{max} (MW)
DG	1	0.008	18.325	30	40	0	50
DG	2	0.0085	25.324	20	20	0	20
V2G	3	0	0.117	0	0	0	50
DR	4	0.02	15.12	0	0	0.5	10
DR	5	0.034	15.12	0	0	0.5	8
DG	7	0.077	30.12	0	0	75	350
DR	8	0.114	17.1	0	0	0.5	2.3
DR	9	0.034	35.2	0	0	0.5	9
DR	10	0.034	18.2	0	0	0.5	9
DG	13	0.075	10.546	30	80	200	590
DG	14	0.0075	8.02	50	150	13	60
DG	15	0.008	6.34	50	140	54	155
DG	16	0.005	4.123	100	300	54	155
DG	18	0.001	1.213	400	800	100	400
V2G	19	0	0.117	0	0	0	50
DR	20	0.074	20.1	0	0	0.5	12
DG	21	0.002	2.678	180	400	100	400
DG	22	0.002	3.231	150	400	200	300
DG	23	0.005	3.451	100	300	108	310

Abbreviations: DG, distributed generation; DR, demand response; V2G, vehicle to grid.

TABLE A2 Status of EVs based on historical data.

No.	SOC	Income	Education level	Wind	Car discharging
1	Medium	High	High	Weak	No
2	Medium	High	High	Strong	No
3	Medium	High	High	Strong	No
4	High	High	High	Weak	Yes
5	Low	Mild	High	Weak	Yes
6	Low	Low	Normal	Weak	Yes
7	Low	Low	Normal	Strong	No
8	High	Low	Normal	Strong	Yes
9	Medium	Mild	High	Weak	No
10	Medium	Low	Normal	Weak	Yes
11	Low	Mild	Normal	Weak	Yes
12	Medium	Mild	Normal	Strong	Yes
13	High	Mild	High	Strong	Yes
14	High	High	Normal	Weak	Yes
15	Rain	Mild	High	Strong	No
16	High	High	Normal	Weak	Yes
17	High	High	Normal	Weak	Yes
18	High	Low	Normal	Strong	Yes
19	High	Low	Normal	Strong	Yes
20	Low	Mild	High	Weak	Yes
21	High	High	Normal	Weak	Yes
22	High	High	Normal	Weak	Yes
23	High	High	Normal	Weak	Yes
24	Low	Mild	High	Weak	Yes

Abbreviations: EV, electric vehicle; SOC, state of charge.