An Intelligent Integrated Approach for Efficient Demand Side Management With Forecaster and Advanced Metering Infrastructure Frameworks in Smart Grid

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ABSTRACT

The development of advanced metering infrastructure (AMI) in smart grid (SG) had enabled consumers to participate in demand-side management (DSM) using the price-based demand response (DR) programs offered by the distribution companies (DISCO). This way, not only the consumers minimize their electricity bills and discomfort, but also the DISCOs can handle peak power demand and reduce the carbon (CO\textsubscript{2}) emissions in a controlled manner. Building an optimization framework that will minimize cost, peak demand, waiting time, and CO\textsubscript{2} emission is not only a challenging task but also a concern of DSM. Most analyses are based on cost and peak-to-average ratio (PAR) minimization, but the effectiveness of the DSM framework is equally determined by user comfort and CO\textsubscript{2} emission. Considering only one objective (cost) or two objectives (cost and PAR) is not sufficient. Thus, for DSM framework to achieve these four relatively independent objectives at the same time, minimized cost, PAR, CO\textsubscript{2} emission, and user discomfort, an energy management controller (EMC) based on our proposed algorithm hybrid bacterial foraging and particle swarm optimization (HBFPSO) is employed that return optimal power usage schedule for consumers. A novel DSM framework consists of four units: (i) DISCO, (ii) multi-layer perceptron (MLP) based forecast engine, (iii) AMI, and (iv) demand-side energy management modules is successfully developed in this work. To validate the proposed model, extensive simulations are conducted and results are compared with the benchmark models like genetic algorithm (GA), bacterial foraging optimization algorithm (BFOA), binary particle swarm optimization (BPSO), and a hybrid combination of genetic and binary particle swarm optimization (GBPSO) in terms of electricity cost, PAR, user comfort, and CO\textsubscript{2} emissions. The simulation results demonstrate effectiveness of our proposed model to outperform all the benchmark models in optimizing the consumer and DISCO objectives. The proposed scheme has reduced electricity cost, user discomfort, PAR, and CO\textsubscript{2} emission for the residential sector by 15.14\%, 4.6\%, 61.6\%, and 52.86\% in scenario 1, 62.60\%, 4.56\%, 60.77\%, and 27.77\% in scenario 2, and 26.03\%, 4.54\%, 63.78\%, and 23.02\% in scenario 3, as compared to without an EMC. Similarly, for commercial sector the proposed HBFPSO algorithm reduces electricity cost, user discomfort, PAR, and CO\textsubscript{2} emission by 11.31\%, 5.5\%, 60.9\%, and 38.18\% in scenario 1, 64.9\%, 5.56\%, 44.08\%, and 58.8\% in scenario 2, 15.31\%, 5.26\%, 78.22\%, and 15.58\% in scenario 3. Likewise, the proposed algorithm also has superior performance for the industrial sector for all the three scenarios.

INDEX TERMS

Smart grids, advanced metering infrastructure, demand side management, energy management controller, price-based demand response program, heuristic algorithms, multi-layer perceptron, forecasting, carbon reduction.

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The world’s growing demand for energy has put its natural resources under immense strain. Fossil fuels meet the bulk of our energy needs, resulting in the emission of greenhouse gases that are adversely affecting our environment and driving climate change. To offset the effects of climate change, the world needs to limit and reduce the emission of greenhouse gases. This can be accomplished by moving towards renewable sources of energy, and a smart grid (SG) that can help in the efficient management of existing energy resources. The SG creates a customer service platform by incorporating information and communication technologies into the electric power grid [1]. Moreover, the incorporation of new technologies like advanced metering infrastructure (AMI) into the SG, enables two-way communication between the smart meter and the utility, which can help to reduce both power consumption and energy costs [2].

The SG enables consumers to schedule their power usage, thereby granting them greater control over their power expenditure by allowing them to reduce their power peak-to-average ratio (PAR), based on real-time pricing (RTP), with an inclined block rate (IBR). Several schemes have been proposed for scheduling domestic power consumption [3].

Several researchers have explored demand-side management (DSM), for instance, in [8], a household equipped with smart appliances, a storage unit, electric vehicles, and photo-voltaic micro-generation is considered. The house- hold’s energy resources are managed in such a way to maximize self-consumption and minimize consumption from the utility. In [9], the authors proposed a strategy to reduce electricity costs by scheduling power usage for both interruptible and uninterruptible loads; but, power demand may create peaks when the electricity price is low. In [6], both electrical and thermal appliances are considered to study the effect of seasonal variations on electricity costs without PAR. In [7], optimal load scheduling is achieved by dynamically scheduling a consumer’s load. However, peak load requirements may emerge in an incentive-based system.

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along with an opportunistic scheduling scheme based on an optimal stopping rule using multiple knapsacks for DSM of smart appliances. It resulted in a model with low complexity and shifted load from on-peak to off-peak hours. In [12], an incentive-based DR strategy is presented, which is very effective in reducing customers’ peak loads and electricity costs. Moreover, weighted particle swarm optimization (PSO) is used to demonstrate the efficiency of the proposed strategy as a practical tool for peak load shaving in the home energy management system (HEMS). Before load scheduling, electrical consumption forecasting is mandatory for efficient energy management to minimize PAR and the total cost of electricity [13]–[15]. Because scheduling with inaccurate load results in high PAR that overloads the power grid and creates threats to power system stability or cause blackouts in the worst case. Several approaches have been proposed to address the optimal in-home power scheduling problem using techniques such as linear programming [16], [17], PSO techniques [18], and meta-heuristic methods [19].

Thus, an intelligent integrated model is developed, which employs EMC-based on our proposed hybrid bacterial foraging and particle swarm optimization (HBFPSO) algorithm for efficient DSM of residential, commercial, and industrial service areas under price-based DR programs in the SG to overcome limitations in the existing literature. The DSM in this study aims to reduce electricity bills, curtail the PAR, and minimize carbon (CO$_2$) emissions while ensuring consumer comfort. The main contributions and highlights of this paper are as follows:

- The forecast engine module based on MLP and AMI module both are coupled with the demand-side energy management module to forecast the demand side load and offered price of the DR program. The purpose is to perform efficient demand-side management via scheduling energy usage profile of demand-side load under the forecasted offered price of the DR program.
- A price-based DR program is introduced that broadcasts three pricing signals, i.e., day-ahead pricing scheme (DA), time of use pricing scheme (ToU), and critical peak pricing scheme (CPP), to the consumers to participate in the DSM to realize peak clipping, valley filling, and demand curve smoothing via load shifting.
- A heuristic algorithm-based environment is introduced to schedule the operation of the demand-side load of three service areas, i.e., residential, commercial, and industrial.
- Different load categories are introduced for the appliances used in residential, commercial, and industrial service areas to ensure implementation of the DSM under price-based DR programs.
- An objective function is mathematically formulated, which is subject to practical energy consumption constraints to perform DSM via scheduling in order to ensure energy and cost savings, alleviate PAR, reduce CO$_2$ emissions, and improve user comfort.
- In [20]–[22] the electricity cost and peak demand load ratio are formulated as an optimization problem, whereas, in this paper in addition to electricity cost and PAR, CO$_2$ emissions and user-comfort are also formulated and investigated by solving the DSM optimization problem via scheduling demand-side load of residential, commercial, and industrial service areas under price-based DR programs.
- A novel HBFPSO algorithm-based EMC is proposed to solve the DSM problem by optimally scheduling load of three service areas like residential, commercial, and industrial.
- The proposed method is evaluated by comparing its performance to four benchmark optimization algorithms like GBPSSO, GA, BFOA, and BPSO in terms of five performance metrics: energy consumption, electricity cost, PAR, user-comfort, and CO$_2$ emissions.
- Simulation results demonstrate that our proposed algorithm significantly reduces electricity costs, alleviates PAR, minimizes CO$_2$ emissions, and reduces consumer’s discomfort.

The remaining sections of the manuscript are organized as follows: Related work is presented in Section II, whereas Section III elaborates the proposed system model. Section IV formulates the problem and presents the proposed solution, whereas the simulation results are detailed in Section VI. Finally, in Section VII, the manuscript is concluded.

II. RELATED WORK

In the SG, demand-side consumers are encouraged to take part in DSM via AMI and home area network (HAN), which has been studied extensively in the existing literature. In [23], reduction in peak demand, and improvement in the losses and voltage profile of a power distribution network are achieved through large scale control of domestic refrigerators without affecting their quality of service. In [24], the authors propose load-shift incentives for household DR and analyze the short and long term effects of exposing customers to hourly spot market prices and a simple rebate scheme. In [26], the authors utilized heuristic-based EMC under hybrid generation in order to reduce electricity costs of households, and conclude that it is mostly affected by the number of people in the house and the surface area of the house. Demand response is an important feature of SG [24], and the authors in [25] also conclude that DR under a variable pricing scheme makes wind power more valuable. In [27], the authors conclude that RTP can be provided to consumers through bidirectional communication between the consumer and the power grid. Besides, they proposed an intelligent opportunistic scheme for scheduling the operation of appliances in off-peak hours to reduce the electricity costs without affecting consumer comfort. The authors in [28] proposed a distributed system
for optimally scheduling power generation units subjected to environmental constraints, dynamic line rating, wind power uncertainty, energy storage unit, and a cross-border energy market. In [29], the authors proposed an economic model for DR to maximize consumer utility under daily consumption constraints. In [35], a dynamic price-based DR is modelled, and then optimized for maximizing profits and user comfort using PSO algorithm. The authors in [36], proposed DSM strategies that adapt two aspects of the DR program into account: price-based and incentive-based programs in order to optimize the energy consumption of consumers. A HEMS is presented in [37] that use a price-based DR program for residential consumers and discusses demand-limit and injection-limit strategies of price-based DR program to improve customer satisfaction. Conventional methods for load scheduling aim either to maximize the consumption payoff or minimize the consumption cost. Therefore, in [38], a cost-efficiency based framework is proposed for residential load scheduling that reflects the user’s consumption behavior and an energy profile that is in terms of cost-efficiency. The authors in [39], proposed a power grid integrated with aggregator and electric vehicles (EV). The load is scheduled under the integrated framework and also energy trading through EV is performed using a game-theoretic approach among self-interested customers. In [40], a household equipped with smart appliances, a storage unit, EV, and photovoltaic micro-generation is considered and resources are scheduled to maximize the use of self-generated energy and minimize the use of borrowed energy from the utility. In [41], an energy management model is proposed to minimize the cost of electricity, consumer discomfort, and peak energy consumption using grey wolf optimized enhanced differential evolution (GWmEDE) algorithm, which combines the grey wolf optimization (GWO) and modified enhanced differential evolution (mEDE) algorithms for optimal energy management. A DSM strategy is proposed in [42] to mitigate electricity costs and improve consumer comfort using heuristic algorithms and multiple knapsacks. In [43], the authors propose bidirectional communication between the consumer and the grid along with an opportunistic scheduling scheme based on an optimal stopping rule for smart appliances resulting in a simpler model and shifting of the load to off-peak hours [11] in the introduction section. In [44], an incentive-based demand response strategy is presented, which is very effective in reducing customers’ peak loads and electricity costs. Moreover, the PSO algorithm is used to demonstrate the efficiency of the proposed strategy as a practical tool for peak load shaving in industries [12]. In [45], a system model is proposed using BPSO to minimize PAR and the total cost of electricity.

In [46], the authors present a model to minimize the electricity costs and maximize comfort for residential consumers by optimizing a Taguchi loss function for a price-based DR program with AMI. In [47], a system model with a non-sorted genetic algorithm (NSGA) is proposed to optimize the daily cost of electricity and user comfort under the RTP price-based DR program. In [48], a system model is proposed to maximize a customer’s utility using the ToU tariff. In [49], a system model is presented for residential load scheduling that allows customization and configuration of parameters such as renewable resources and hybrid electrical storage systems (HESS) and improves cost savings by up to 45%. In [50], an advanced HEMS is proposed with non-intrusive load monitoring (NILM) to reduce PAR and improve user comfort.

In the aforementioned related work, the authors did not utilize completely the favorable features of the SG like AMI enabling bi-directional communication and automatic control. Some authors minimized electricity cost, few focused on PAR, and some catered both electricity cost and PAR while some authors worked on only user comfort. However, the performance parameters under discussion were not catered by any author simultaneously. Furthermore, multiple service areas and different pricing signals were not considered simultaneously in the literature. Thus, in this study, the four performance parameters like electricity cost, CO₂ emission, PAR, and user-comfort are considered simultaneously in the context of DSM under price-based DR programs for multiple service areas.

III. THE PROPOSED SYSTEM MODEL FOR DEMAND-SIDE MANAGEMENT UNDER PRICE-BASED DR PROGRAMS

In this study, an intelligent model is proposed for efficient energy management, which is an integrated framework of four modules like power company module, forecast engine module, AMI module, and demand-side energy management module as illustrated in Figure 1. This work is an extension of our previous conference paper published in [51]. The focus of the earlier work is only on the DSM of residential service area while the current work is for the DSM of three service areas like residential, commercial, and industrial with two novel frameworks of forecaster and AMI in SG. The proposed model is a modular framework of four modules connected in a cascaded manner, where the output of the succeeding module is the input for the proceeding module as depicted in Figure 1. Before performing the DSM of three service areas, it is imperative to identify the factors that influence DSM. These influencing factors include the energy consumption profile of residential, commercial, and industrial service areas, available energy generation profile, price-based DR programs, and weather and environment of the area, where this model is to be implemented. However, it is not practical to consider all factors and parameters at the same time because they complicate the process and also degrade the model performance. Thus, in this study, price-based DR programs and energy consumption profiles of residential, commercial, and industrial service areas are selected from the pool of factors and parameters essential for DSM. As the focus of this study is on efficient DSM of residential, commercial, and industrial service areas, therefore, before DSM, a proper forecast engine is required to accurately forecast both energy consumption profile of demand-side (residential,
TABLE 1. A summary of related work in terms of techniques, objectives, features, and limitations in the context of DSM under price-based DR programs in SG.

| Techniques                                      | Objectives                                         | Features                                                           | Limitations                                      |
|-------------------------------------------------|----------------------------------------------------|--------------------------------------------------------------------|-------------------------------------------------|
| [23]Thermo-dynamic modeling                     | Reduction of peak demand                          | Flexible disconnected without impacting negatively on their delivered service | Cost minimizing is not considered               |
| [24]Simple rebate scheme                        | Load shifting to off-peak hours                   | Load-shift incentives for household DR                             | User comfort is not considered                  |
| [25]Opportunistic scheduling scheme             | Load-shift, user comfort, and electricity bill    | Bidirectional communication to power grid                         | System complexity is increased                  |
| [26]Decentralized methodology                  | Energy saving and reduce electricity bill         | Regional location is the most important factor                    | PAR is not considered                           |
| [28]Gauss-siedel                                | Energy saving                                     | Presence of wind power and storage system                         | Wind power is not reliable                      |
| [29]Decomposition algorithm                     | Maximize customer utility                         | Cross-period shift in consumption pattern of individual consumer  | Electricity bill                                |
| [30]MINLP                                       | Cost minimization                                 | Consumer can shift appliances uses in order to get incentives     | User comfort is not considered                  |
| [31]TOU tariff with IBR                         | Cost reduction and comfort                        | User can use appliances on priority based                         | Peak load is not considered                     |
| [32]HEMDAS                                      | Minimize cost and avoid peak load demand          | System can store and generate electricity                         | Uncertainty of PV system is not considered      |
| [33]UEP compare with RTP system                 | Reduction in cost and peak load                  | Energy storage system is used to store electricity in low peak hours | User comfort                                    |
| [34]DRLS based on ACPs                         | Cost and peak load reduction                      | Price remain same in one CL.                                      | No limit on energy consumption                  |
| [35]GA                                          | Cost and PAR reduction                            | Optimization problem is formulated time slot is changed to control PAR and cost | System complexity is increased                  |
| [36]PSO algorithm                               | Cost minimizing and user comfort                  | Optimization modeling for dynamic price-based DR                  | PAR is not considered                           |
| [37]BPSO algorithm                              | Cost minimizing and user comfort                  | DSM strategies                                                    | Complexity increased                            |
| [38]MINLP                                       | Minimizing cost                                   | Demand-limit-based DR and injection-limit-based DR                | User comfort                                    |
| [39]GA                                          | Electricity consumption                           | Novel concept of cost efficiency-based residential load scheduling | Cost minimizing                                |
| [40]Heuristic algorithm                         | Energy trading using EVs                         | Novel electricity load scheduling algorithm                       | User comfort                                    |
| [41]Dynamic programming                         | Minimizing the cost of energy consumption        | Photovoltaic micro-generation                                      | PAR is not considered                           |
| [42]Stochastic and robust optimization          | minimizing electricity cost                     | Real-time-price-based DR program                                  | PAR and user comfort are not considered         |
| [44]Opportunistic scheduling                    | Low complexity and shifting load from peak to off-peak hours | Optimal stopping rule for smart appliances and automation control | Cost minimizing is not considered               |
| [47]AMT and Taguchi loss function                | Minimize cost and maximize user comfort           | Considering power scheduling problem                              | PAR is not considered                           |
| [48]Task management methodology and evolutionary algorithm | Minimize cost and maximize user comfort             | System model having NSGA                                           | PAR is not considered                           |
| [49]TOU with DR program                         | User comfort                                      | System model having NSGA                                           | PAR and cost are not considered                 |
| [50]GA with IBR                                 | Decrease peak load curve                         | Dynamic residential load scheduling                                | User comfort and cost are not considered        |
| [51]Relaxation technique                        | Complex scheduling problem                        | Renewable resources and hybrid electrical storage systems          | Complexity increases                            |
| [52]GA                                          | PAR and user comfort                              | Multi-objective in-home power scheduling mechanism is proposed    | Reduction of cost is not considered             |

commercial, and industrial service areas) and price-based DR programs offered pricing signals beforehand in order to ensure efficient DSM. Thus, a multi-layer perceptron (MLP) based forecast engine receives historical electrical energy consumption data and historical price-based DR programs offered pricing signals. The MLP-based forecast engine forecast the energy consumption profile of demand-side and price-based DR programs offered prices beforehand based.
on the received historical data. The AMI module receives forecasted energy consumption profile of demand-side and price-based DR programs offered prices via the CM and deliver both energy consumption and offered price profiles to the demand-side energy management module. The HBF-PSO algorithm-based EMC of demand-side energy management module utilized energy consumption and offered price profiles and perform efficient DSM via load scheduling. The detail description of the proposed system model is as follows:

A. MLP-BASED FORECAST ENGINE MODULE

The MLP-based forecast engine in this study is selected due to its ability to capture the non-linear mapping between input and output. The proposed forecast engine drive on supervised learning and history data. Thus, the proposed MLP-based forecast engine is empowered by training and learning to forecast demand-side energy consumption profile and price-based DR programs offered price profile. The dataset used for the training of MLP-based forecast engine is received from the power company module and is taken form midwest independent system operator (MISO) under federal energy regulatory commission (FERC) [55]. The dataset consists of historical energy consumption patterns of residential, commercial, and industrial service areas, and a price-based DR program offered prices like DA, ToU, and CPP during the period of one year from August 2006 to August 2007. The dataset is first pre-processed via data cleansing operation in order to recover missing and defective values by replacing with an average of the previous days’ values. The clean data is divided into three sets like training set, testing set, and validation set. The training data is employed to train the MLP-based forecast engine, which has three layers layout: input layer (1), hidden layer (2), and the output layer (1). The MLP-based forecast engine is a feed-forward network having a fully connected layer, where the neurons of the proceeding layer are connected to the neurons of the succeeding layer through synaptic weights, as illustrated in Figure 2.

The MLP-based forecast engine takes \( z(t) \) input vector from historical dataset and map the input vector \( z(t) \) to the output vector \( F(t) \). The output of the MLP-based forecast engine is as follows:

\[
F(t) = \sum_{i=1}^{n} W_i f(y_i) + \sum_{j=1}^{m} \beta_j z_j ;
\]

where,

\[
f(y_i) = \frac{1}{1 + \exp(-y_i)}
\]

The output vector \( F(t) \) represents day-ahead forecasted results of energy consumption profile of demand side and price-based DR programs offered price profile, \( W_i \) represents weight factor from input node towards output nodes, \( \beta_j \) represents linear weight form input node towards output nodes, \( z_j \) denotes input elements, and \( y_i \) is the input for hidden nodes.

The MLP-based forecast engine is trained with sigmoidal activation function and Levenberg–Marquardt optimization algorithm. The \( y_i \) is calculated as follows:

\[
y_i = \sum_{j=1}^{3} w_{ij} z_j + b_i,
\]

where, \( w_{ij} \) is the weight from input neurons towards hidden layer, and \( b_i \) represents the value bias that added at hidden layer. The learning process iterates for a number of epochs to train the MLP-based forecast engine. The learning process stop in two ways either when algorithm stopping criterion meet or maximum number of iteration reached. The error function returned after learning process is give as follows:

\[
E = \frac{1}{N} \sum_{k=1}^{N} (A_k - F_k)^2,
\]

where \( F_k \) is the forecasted value (energy consumption profile of demand-side and price-based DR programs offered price profile) result and \( A_k \) is the actual value of (energy consumption profile of demand-side and price-based DR programs offered price profile) at \( k \)th pattern for \( N \) number of employed data samples. The forecasted energy consumption profile of residential, commercial, and industrial service areas and price-based DR programs offered price profile is fed as an input to the AMI module.

B. ADVANCED METERING INFRASTRUCTURE MODULE

The AMI framework is an integrated framework of a data concentrator, a communication module (CM), and meter data management system (MDMS) as depicted in Figure 1. The AMI framework has two CMs; the first one on the consumer side and the other one on the power company side as illustrated in Figure 1. The smart meters are capable of delivering collected and recorded energy consumption data to the AMI framework via the CM. The energy consumption data is received by DC and fed to the MDMS. The MDMS analyzes the received energy consumption data and extracts useful information from the data. The extracted favorable information is delivered to the DISCO via the CM. The detailed and useful information provided by AMI in real-time empowers the DISCO to measure the electricity bill, support better power outage detection, address power grid deficiencies, and improve management and maintenance of assets. The DISCO provides price-based DR programs to AMI to encourage consumers’ participation in price-based DR programs for DSM via scheduling their energy usage pattern in order to reduce electricity, PAR, and other environmental impacts like carbon emission, etc. The DISCO also can turn ON and OFF household appliances in consumer premises to optimize energy consumption. Thus, the AMI acts as a bi-directional communicator between DISCO and consumers and deliver information to and from DISCO and consumers, respectively. This study focuses on
the DSM under price-based DR programs via load scheduling of residential, commercial, and industrial service areas. Therefore, in this case, the DISCO would not control demand-side load remotely but deliver forecasted price-based DR programs to the consumers via AMI to actively participate in DSM.
C. DEMAND-SIDE ENERGY MANAGEMENT MODULE

The demand-side energy management module comprises smart meter, energy management controller (EMC), appliances of residential, commercial, and industrial service areas, in-door display (IDD), and remote control unit laptop or mobile as illustrated in Figure 1. The smart meter acts as an in-door gateway and its vital role is to collect energy consumption data and deliver collected data to AMI and received information from DISCO via AMI to EMC. The smart meter can also communicate with IDD via HAN to enable consumers to view their energy usage. The EMC acts as central neurons in this study and is based on our proposed HBFPSO algorithm in order to perform efficient DSM under price-based DR programs via load scheduling of three service areas. The HBPSO algorithm-based EMC takes forecasted price-based DR programs via load scheduling of three service areas. The HBPSO algorithm-based EMC would schedule is discussed in the succeeding subsection.

The load that HBFPSO-based EMC would schedule is categorized as follows:

1) LOAD CATEGORIZATION

As illustrated in Fig. 4, we consider three service areas or sectors on the demand side, i.e., residential, commercial, and industrial, where each sector has \( N \) number of loads.

a: RESIDENTIAL SECTOR

The residential sector’s load is further categorized into the following three types based on the flexibility either in time or power:

1) Portable Interruptible Load,
2) Portable Un-interruptible Load,
3) Consistent Load

Table 2 shows the detailed description of load classification corresponding to appliances. Let \( A_r = A_p \cup A_{pni} \cup A_r \) represent a set of residential sector appliances, where \( A_p \), \( A_{pni} \), and \( A_r \) represent portable interruptible, portable un-interruptible and consistent appliances type, respectively. The time horizon in which these appliances operate is 24h time horizon, defined as \( T = \tau_1, \tau_2, \tau_3 \ldots \ldots \tau_{24} \).

b: PORTABLE INTERRUPTIBLE LOAD

The portable interruptible load includes appliances like the cooking range, personal computers, water pump, microwave oven, and electric iron. We assume that their operation can be interrupted and they can be scheduled to operate at any time. Let \( A_{pir} \) be the set of portable interruptible appliances and \( a_{pir}^r \in A_{pir} \) represent each appliance in the set with \( \lambda_{pir}^r \) as its power rating. The total energy consumption per day for the portable interruptible load \( \varepsilon_{pir}^r \) can be given by (5).

\[
\varepsilon_{pir}^r = \sum_{a_{pir}^r \in A_{pir}^r} \left[ \sum_{\tau=1}^{T} \lambda_{pir}^r \times \alpha(\tau) \right]
\]  

The total cost of electricity consumed by the portable interruptible for residential appliances over the time period \( T \) can be obtained using (6).

\[
\sigma_{pir}^r = \sum_{a_{pir}^r \in A_{pir}^r} \left( \lambda_{pir}^r \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T
\]  

In order to minimize the total cost of electricity consumed, we minimize the cost per hour electricity consumed as given in (7).

\[
\sigma_{pir}^r = \sum_{a_{pir}^r \in A_{pir}^r} \left( \lambda_{pir}^r \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T
\]  

The total cost of operating the portable un‐interruptible residential load for an entire day is given by (9).

\[
\sigma_{pni}^r = \sum_{a_{pni}^r \in A_{pni}^r} \left( \lambda_{pni}^r \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T
\]  

whereas the hourly cost of operating these residential appliances is given by (10).

\[
\sigma_{pni}^r = \sum_{a_{pni}^r \in A_{pni}^r} \left( \lambda_{pni}^r \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T
\]
d: CONSISTENT LOAD

Appliances such as refrigerator, water dispenser, and fans etc. are categorized as consistent load as they are required to operate almost all the time. Let $A_c$ be the set of appliances of the consistent load category, and let $a_c \in A_c$ represent individual appliance in this set with power rating $\lambda_c$. Then, the daily energy consumption $\varepsilon_r^c$ for this set of appliances is given by (11).

$$\varepsilon_r^c = \sum_{a_c \in A_c} \left[ \sum_{\tau=1}^{T} \lambda_c^\tau \times \alpha(\tau) \right]$$ (11)

The cost of operating the consistent residential load over a time period $T$ is given by (12).

$$\varsigma_{\text{total}r}^c = \sum_{a_c \in A_c} \left[ \sum_{\tau=1}^{T} \lambda_c^\tau \times \rho(\tau) \times \alpha(\tau) \right]$$, (12)

whereas, the cost per hour for operating the consistent residential load can be calculated using (13).

$$\sigma_{c}^{r} = \sum_{a_c \in A_c} \left( \lambda_c^\tau \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T \quad (13)$$

The total load for the residential sector is represented by $\gamma_R$, and can be calculated over a time period $T$ using (14).

$$\gamma_R = \varepsilon_{\text{p}i}^r + \varepsilon_{\text{pn}i}^r + \varepsilon_c^r$$, (14)

The HBFPSO algorithm-based EMC (see Algorithm 3) perform DSM for residential service area under price-based DR program via load scheduling and the returned optimal energy consumption schedule for each appliances in each time interval is given in (15).

$$N_r^{r} = \begin{bmatrix} Y_{\text{api}}^{r1} & Y_{\text{api}}^{r1} & Y_{c}^{r1} \\ Y_{\text{api}}^{r2} & Y_{\text{api}}^{r2} & Y_{c}^{r2} \\ Y_{\text{api}}^{r3} & Y_{\text{api}}^{r3} & Y_{c}^{r3} \end{bmatrix}$$ (15)
2) COMMERCIAL SECTOR
According to the consumers operating behavior the commercial sector load is divided into the following two categories:

1) Portable Un-interruptible
2) Consistent load

Examples of appliances belonging to these categories along with their power ratings are given in Table 3. Let $A_c = A_{pmi} \cup A_c$ represent a set of appliances, where $A_{pmi}^c$ and $A_c^c$ represent the portable un-interruptible and consistent appliances, respectively. This categorization is based on commercial consumers requirement over a 24h time horizon, complete horizon is defined as $T = \tau_1, \tau_2, \tau_3 \ldots \ldots \tau_{24}$.

a: PORTABLE UN-INTERRUPTIBLE LOAD
The portable un-interruptible load includes appliances like washing machines, cooking ranges, microwave ovens, and blenders. The appliances of this category is assumed not to be interrupted during operation but can be operated at any time. Let $A_{pmi}^c$ be the set of un-interruptible appliances and let $a_{pmi}^c \in A_{pmi}^c$ represent an appliance in this set with a power rating $\lambda_{pmi}^c$. The total daily energy consumption $\varepsilon_{pmi}^c$ for this set of appliances can be calculated using (16).

$$\varepsilon_{pmi}^c = \sum_{a_{pmi}^c \in A_{pmi}^c} \left[ \sum_{\tau=1}^{T} \lambda_{pmi}^c \times \alpha(\tau) \right]$$ (16)

The daily cost of operating these commercial appliances is given by (17),

$$\varepsilon_{pmi}^{\text{total}} = \sum_{a_{pmi}^c \in A_{pmi}^c} \left[ \sum_{\tau=1}^{T} \lambda_{pmi}^c \times \rho(\tau) \times \alpha(\tau) \right],$$ (17)

whereas the hourly cost of operating these commercial appliances can be determined using (18),

$$\sigma_{pmi}^{\tau} = \sum_{a_{pmi}^c \in A_{pmi}^c} \left( \lambda_{pmi}^c \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T$$ (18)

b: CONSISTENT LOAD
Appliances such as freezers, chillers, water dispensers, security systems, and fans etc. are categorized as consistent load appliances since they are required to operate almost all the time. Let $A_c^c$ denote the set of consistent load appliances and let $a_c^c \in A_c^c$ represent an individual appliance in this set with a power rating of $\lambda_c^c$. Then, the total daily energy consumption $\varepsilon_c^c$ for this set of appliances can be calculated using (19).

$$\varepsilon_c^c = \sum_{a_c^c \in A_c^c} \left[ \sum_{\tau=1}^{T} \lambda_c^c \times \alpha(\tau) \right]$$ (19)

The cost of operating these commercial appliances over a time period $T$ can be calculated using (20),

$$\varepsilon_c^{\text{total}} = \sum_{a_c^c \in A_c^c} \left[ \sum_{\tau=1}^{T} \lambda_c^c \times \rho(\tau) \times \alpha(\tau) \right],$$ (20)

whereas, the hourly cost of operating these commercial appliances can be determined using (21).

$$\sigma_c^{\tau} = \sum_{a_c^c \in A_c^c} \left( \lambda_c^c \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T$$ (21)

The total load for the commercial sector, $\gamma_c$, over a time period $T$ can be calculated using (22).

$$\gamma_c = \varepsilon_{pmi}^c + \varepsilon_c^c,$$ (22)

The HBFPSO algorithm-based EMC (see Algorithm 3) perform DSM for commercial service area under price-based DR program via load scheduling and the returned optimal energy consumption schedule for each individual appliances in each time interval is given in (23):

$$N_c = \begin{bmatrix} \gamma_{c_{\tau_1}}^{1} & \gamma_{c_{\tau_2}}^{1} & \gamma_{c_{\tau_3}}^{1} \\ \gamma_{c_{\tau_1}}^{2} & \gamma_{c_{\tau_2}}^{2} & \gamma_{c_{\tau_3}}^{2} \\ \gamma_{c_{\tau_1}}^{3} & \gamma_{c_{\tau_2}}^{3} & \gamma_{c_{\tau_3}}^{3} \end{bmatrix}$$ (23)

3) INDUSTRIAL SECTOR
The industrial sector’s load is divided into the following two categories:

1) Portable interruptible
2) Consistent load

Examples of appliances belonging to these categories along with their power ratings are given in Table 4. Let $A_i = A_{mi} \cup A_i$ represent a set of appliances, where $A_{mi}$ and $A_i^c$ denote appliances of portable interruptible and consistent load types, respectively. The categorization of these appliances is based upon industrial power requirement over a 24h time horizon $T = \tau_1, \tau_2, \tau_3 \ldots \ldots \tau_{24}$. 

---

**Table 3. Description and categorization of appliances for the commercial sector.**

| Group                  | Appliances        | Power rating (kW) | Daily usage (h) |
|------------------------|-------------------|-------------------|-----------------|
| Portable un-interruptible | Cooking range    | 0.40              | 6               |
|                        | Computer          | 0.35              | 8               |
|                        | Water purifier    | 0.9               | 4               |
|                        | Microwave         | 0.25              | 8               |
|                        | Blender           | 0.30              | 2               |
|                        | Washing machine   | 2.50              | 3               |
|                        | Iron              | 1.00              | 2               |
| Consistent appliances  | Fire alarm        | 0.50              | 15              |
|                        | Security camera   | 0.50              | 14              |
|                        | Fan               | 0.5               | 7               |
**a: PORTABLE INTERRUPTIBLE LOAD**

The portable interruptible load includes appliances like the water dispensers, kettles, lights, and vacuum cleaners. It is assumed that their operation can be interrupted and they can be scheduled to operate at any time. Let \( A^i_{pi} \) be the set of portable interruptible appliances and \( d^i_{pi} \in A^i_{pi} \) represent each appliance in the set with \( \lambda^i_{pi} \) as its power rating. The total energy consumption per day for the portable interruptible load \( \epsilon^i_{pi} \) can be calculated using (27).

\[
\epsilon^i_{pi} = \sum_{d^i_{pi} \in A^i_{pi}} \left[ \sum_{\tau=1}^{T} \lambda^i_{pi} \times \alpha(\tau) \right] \tag{24}
\]

The total daily cost of electricity for all the portable interruptible industrial appliances over a time period \( T \) is given by (25),

\[
\sigma^i_{pi} = \sum_{d^i_{pi} \in A^i_{pi}} \left[ \sum_{\tau=1}^{T} \lambda^i_{pi} \times \rho(\tau) \times \alpha(\tau) \right] \forall \tau = 1 : T \tag{25}
\]

where, \( \rho(\tau) \) represents the price signal and \( \alpha(\tau) \in [0, 1] \) denotes the state of an appliance, i.e., ON or OFF. Similarly, the hourly cost of electricity for interruptible industrial appliances is given by (26), which can be minimized in order to reduce the total costs.

\[
\sigma^i_{pi} = \sum_{d^i_{pi} \in A^i_{pi}} \left( \lambda^i_{pi} \times \rho(\tau) \times \alpha(\tau) \right) \forall \tau = 1 : T \tag{26}
\]

**b: CONSISTENT LOAD**

Appliances such as motors, welding machines, and arc furnaces are categorized as consistent load appliances since they are required to operate almost all the time. Let \( A^i_c \) denote the set of consistent load appliances and let \( d^i_c \in A^i_c \) represent an individual appliance in this set with a power rating of \( \lambda^i_c \). Then, the total daily energy consumption, \( \epsilon^i_c \), for this set of appliances can be calculated using (27).

\[
\epsilon^i_c = \sum_{d^i_c \in A^i_c} \left[ \sum_{\tau=1}^{T} \lambda^i_c \times \alpha(\tau) \right] \tag{27}
\]

The cost of operating these industrial appliances over a time period \( T \) can be calculated using (28),

\[
\sigma^i_{total} = \sum_{d^i_c \in A^i_c} \left[ \sum_{\tau=1}^{T} \lambda^i_c \times \rho(\tau) \times \alpha(\tau) \right] \tag{28}
\]

whereas, the hourly cost of operating these industrial appliances can be determined using (29).

\[
\sigma^i_{c} = \sum_{d^i_c \in A^i_c} \left( \lambda^i_c \times \rho(\tau) \times \alpha(\tau) \right) \forall \tau = 1 : T \tag{29}
\]

Let \( \gamma^i_1 \) denote the total load of the industrial sector over a time period \( T \), then it can be determined using (30) as follows:

\[
\gamma^i_1 = \epsilon^i_{pi} + \epsilon^i_{c} \tag{30}
\]

**IV. PROBLEM FORMULATION AND THE PROPOSED SOLUTION**

The primary objective of most DSM strategies is to minimize consumers’ electricity costs by minimizing the PAR, which is

### TABLE 4. Description and categorization of appliances in the industrial sector along with their power ratings.

| Group                  | Appliances       | Power rating (kW) | Daily usage (h) |
|------------------------|------------------|------------------|-----------------|
| Portable interruptible | Water dispenser  | 2.50             | 5               |
|                        | Kettle           | 3.00             | 6               |
|                        | Lights           | 2.00             | 8               |
|                        | Vacuum cleaner   | 0.40             | 6               |
| Consistent appliances  | Water heater     | 0.40             | 6               |
|                        | DC motor         | 2.50             | 9               |
|                        | Welding machine  | 3.6              | 11              |
|                        | Arc furnace      | 4.00             | 12              |
|                        | Fan              | 1.00             | 9               |
|                        | Induction motor  | 5.00             | 8               |

The HBFPSSO algorithm-based EMC (see Algorithm 3) perform DSM for industrial sector under price-based DR program via load scheduling and the returned optimal energy consumption schedule for each individual appliances in each time interval is given by (31),

\[
N_{ij} = \begin{bmatrix} \gamma_{api}^{r1} & \gamma_{api}^{r1} \\ \gamma_{api}^{r2} & \gamma_{api}^{r2} \\ \gamma_{api}^{r3} & \gamma_{api}^{r3} \end{bmatrix} \tag{31}
\]

4) ENERGY COST AND UNIT PRICE

The total energy cost can be calculated by first determining the unit price using a pricing scheme such as DA, CPP, and ToU. In this study, however, we use dynamic prices represented by the signal, \( \rho(\tau) \), which varies for each time interval \( \tau \in T \). For each time interval \( \tau \), first the value of price signal, i.e., \( \rho(\tau) \) is determined and then it is multiplied with the total energy consumed during that period of time to calculate the cost of electricity for that interval. Equation (32) gives the relation for calculating the hourly cost of all appliances.

\[
\sigma^i_{total} = \sum_{a_i \in A_a} \gamma(\tau, a_i) \times \rho(\tau) \forall \tau = 1 : T \tag{32}
\]

Similarly, the daily energy cost can be calculated if we sum up the value of 32 for all the appliances over all the time intervals in \( T \) as given in (33).

\[
\sigma_{total} = \sum_{\tau=1}^{T} \left[ \sum_{a_i \in A_a} \gamma(\tau, a_i) \times \rho(\tau) \right] \tag{33}
\]
generally done by shifting load from peak to off-peak hours. In this paper, we propose a HBFPSO algorithm EMC that participate in DSM under price-based DR programs. This participation not only reduces the PAR, consumers’ electricity costs, but also ensures users’ comfort while minimizing their carbon footprint.

A. PROBLEM FORMULATION

We proposed HBFPSO algorithm-based EMC for DSM of three service areas under price-based DR programs that aims to achieve the following objectives: reduction in a consumer’s electricity costs, alleviation of the PAR, maximization of consumer’s comfort, and reduction of a consumer’s carbon footprint. The HBFPSO algorithm-based EMC achieve these objectives by scheduling demand side load. Through scheduling the HBFPSO algorithm-based EMC shifts the load form on-peak hours to off-peak hours while preserving consumers comfort. The objective function that we seek to minimize is mathematically modeled as minimization problem and defined in (34) as:

$$\text{min} \left( \sum_{t=1}^{T} \left( \sum_{a \in A} (\gamma_{t,a}) \times \rho(\tau) \right) + CO_2 + Delay + PAR \right)$$

(34)

where,

$$PAR = \max_{t \in T} \left( \frac{1}{T} \sum_{t=1}^{T} |\gamma_t| \right) \leq E_{\text{max}}$$

(35)

$$CO_2^{\text{Per hour}} = \left( \frac{\text{Avg}/\text{price}(\text{Per hour})}{*1.37} \right) * 30$$

(36)

$$\text{Delay} = \frac{\text{sum}(|tA1 - tA2|)}{\text{sum}(tA2)}$$

(37)

Similarly, the constraint in (39) guarantees that the power consumption remains the same before and after scheduling.

$$\sum_{t=1}^{T} |\gamma_t|^{\text{unsch}} = \sum_{t=1}^{T} |\gamma_t|^{\text{sch}}$$

(41)

Furthermore, the constraint in (40) ensures that the total demand load of each group of appliances is less than or equal to the grid capacity (kW). The proposed HBFPSO-based EMC tries to minimize objective function subjected to these constraints for the DSM environment of the SG considering three service areas.

V. THE PROPOSED AND BENCHMARK ALGORITHMS FOR DSM OF THREE SERVICE AREAS UNDER PRICE-BASED DR PROGRAMS

In the literature, various techniques have been proposed to solve the DSM problem via load scheduling under price-based DR programs. Since the DSM problem is highly non-linear, and all linear methods are unable to solve such problems. Thus, we proposed and employed heuristic algorithms to solve the DSM problem via load scheduling of three service areas under price-based DR programs. Heuristic algorithms use two methods to generate an initial population such as random initialization and heuristic initialization. The first method initializes the initial population with completely random solutions. Random solutions are the ones having large diversity, which leads to generating optimal population. The second method initializes the initial population using known heuristic for the problem. The known heuristic has similar solutions and little diversity, which effects the initial fitness of the population. The heuristic initialization leads to some good solutions initially and then fills up the rest of the population with random solutions. Thus, in this study, our focus is to solve the DSM problem by optimal load scheduling under price-based DR programs. Therefore, we conducted random initialization for the proposed and existing algorithms to return optimal load scheduling for solving the DSM problem of three service areas. For more in-depth understanding interested readers are directed to study [52]. Before presenting the proposed algorithm, first, we give a brief description of some benchmark heuristic algorithms in the subsequent text.

A. BACTERIAL FORAGING OPTIMIZATION ALGORITHM

The bacterial foraging optimization algorithm (BFOA) is inspired by the social behavior of bacteria, which swim in search of nutrients and try to find the best nutrients (solutions) to maximize their energy. The BFOA involves the following three phases:

1) Chemotaxis, which simulates the movement of bacteria either through swimming or tumbling. The bacteria
can swim in a single direction or they can tumble and change the direction of their movement. The bacteria alternate between these two types of movements for their entire lifetime.

2) **Reproduction**, which simulates the multiplication of healthy bacteria, and the subsequent replacement of unhealthy bacteria, i.e., those which yield a poor value of the objective function with the healthier ones to maintain a constant population.

3) **Elimination-dispersal**, which simulates the changes in the population of bacteria due to abrupt changes in the environment that can eliminate a fraction of the bacterial population or disperse it into a new location. During this phase, an initial population of bacteria is randomly generated, which is then simulated to swim and tumble around. After each run, the value of the fitness function is calculated for each bacterium in the population. During chemotaxis, the step size $C_i$ should be carefully selected as it affects the algorithm’s ability to converge to an optimal value, i.e., generally, a smaller value leads to a more optimal solution at the expense of more computational time. In the reproduction phase, the healthy bacteria with better values of the fitness function multiply their number by two and replace an equal number of the least healthy bacteria to maintain a constant swarm population. The reproduction phase helps in accelerating the convergence of the algorithm towards a local optimum. The elimination-dispersal phase helps in finding out a globally optimal solution, by eliminating a given bacterium in the population with the probability $P_{ed}$ and replacing it with a new bacterium initialized over the search space. The step by step procedure of this algorithm is illustrated in flowchart Fig. 5. The parameters used for this algorithm implementation are listed in Table 5.

### TABLE 5. The parameters of the BFOA along with their values used in simulations.

| Parameters | Values |
|------------|--------|
| Ne         | 24     |
| Nr         | 5      |
| NC         | 5      |
| Np         | 30     |
| Ns         | 2      |
| Ci         | 0.01   |
| $\Theta$   | 0.5    |
| $Ped$      | 0.5    |
| Maximum generation | 14 |

**B. GENETIC ALGORITHM**

Genetic algorithm (GA) is another biologically inspired nonlinear optimization technique, which is rooted in the concepts of natural selection of living organisms, i.e., living organisms with characteristics that are best suited to their environment will thrive more, compared to those with less suitable characteristics which ultimately go extinct over multiple generations. Biologically, the characteristics of living organisms are determined by the genes located on their chromosomes. GA mimics the biological process of transfer of genetic information from the parent to the offspring, and the selection of the best offspring to replace less suitable chromosomes in the population using some fitness function. Parent chromosomes transfer genetic information to their offspring using **crossover** and **mutation**. In crossover, fractions of two-parent chromosomes mutually transfer genetic material at randomly selected points, whereas in mutation certain randomly selected genes on the parent chromosome undergo a random change as shown in Fig. 6. The mutation occurs with a certain probability, which is usually very low and in our case, it is calculated using (42). It starts with an initial population of chromosomes. Each chromosome encodes the ‘ON’ and ‘OFF’ state of all the appliances using a single bit, i.e., 1 or 0, where 1 represents the ‘ON’ and 0 represents the ‘OFF’ state of an appliance. The new chromosomes that are created after mutations and crossovers between the parent chromosomes are tested using a fitness function. Chromosomes with the optimal fitness function values are retained in the population, whereas those with poor values are removed. This process is iterated over multiple generations to
get the best chromosome population according to the fitness function. The algorithm terminates if the population of chromosomes has converged, i.e., offspring in the new generation is not significantly different than the previous. The step by step procedure of GA to implement for the DSM is depicted in Fig. 6. Furthermore, the parameters of GA that are used in simulations are listed in Table 6 along with their values.

\[ p_m = 1 - p_c \]  \hspace{1cm} (42)

The values and description of different parameters used for the GA are given in Table 6.

**TABLE 6.** The GA parameters along with their values for DSM in SG.

| Parameters     | Values |
|----------------|--------|
| Population size| 20     |
| n              | 10     |
| Number of iteration | 19          |
| \( P_c \) | 0.9 |
| \( P_m \) | 0.1 |

**C. BINARY PARTICLE SWARM OPTIMIZATION ALGORITHM**

Binary particle swarm optimization (BPSO) algorithm is inspired by birds’ flocking in search of food. It is the binary variant of PSO, and is generally used to solve computationally hard optimization problems. The BPSO algorithm is illustrated in Fig. 7. In a flock or swarm, each bird has a certain position and velocity, both of which change according to neighboring birds in the flock. In the problem under our consideration, we use the position matrix to represent the ON-OFF status of appliances, whereas the velocity matrix is used to control the population generation. The velocity function of each swarm is given by (43).

\[ v_i = V_{\text{max}} \times 2(\text{rand}(\text{swarm}, n) - 0.5) \]  \hspace{1cm} (43)

A fitness function is the objective function used to evaluate the different operational status vectors of the appliances over different time intervals in order to determine the status vector that will minimize the cost of electricity, carbon emission, user-discomfort, and PAR. The velocity function is updated using (44),

\[ v[i] = v[i] + c1 \times \text{rand()} \times (pbest[i] - present[i]) + c2 \times \text{rand()} \times (gbest[i] - present[i]), \]  \hspace{1cm} (44)

whereas, (45) is used to update the particle position as follows:

\[ \text{Present}[i] = \text{Present}[i] + v[i] \]  \hspace{1cm} (45)

The velocity function in (43) is real-valued and is converted into binary using the function in (46).

\[ \text{Sig}(j, i) = \frac{1}{1 + e^{-v_{\text{new}}}} \]  \hspace{1cm} (46)

The BPSO algorithm, as illustrated in Fig. (7), iterates until it finds the optimal schedule for powering the appliances. The parameters and values of the BPSO algorithm used in this study are given in Table 7.

**TABLE 7.** The parameters along with their tuned values of the BPSO algorithm used for DSM.

| Parameters     | Values |
|----------------|--------|
| Swarm size     | 10     |
| n              | 10     |
| Number of iteration | 60          |
| \( c_1 \)     | 2      |
| \( c_2 \)     | 2      |
| \( w_1 \)     | 2      |
| \( w_2 \)     | 0.4    |
| \( V_{\text{max}} \) | 4         |
| \( V_{\text{min}} \) | -4       |
is applied, whereas in the second phase the GA operators of crossover and mutation are applied to the gbest values obtained in the first phase. The motivation behind developing a hybrid of GA and BPSO is discussed in detail in [53]. The interested readers are referred for in-depth understanding.

**E. OUR PROPOSED HYBRID BACTERIAL FORAGING AND PARTICLE SWARM OPTIMIZATION ALGORITHM**

First, we proposed the hybrid bacterial foraging and particle swarm optimization (HBFPSO) algorithm, which applies the key steps of BFOA and on the optimal result returned from the BPSO algorithm. The motivation behind this hybrid algorithm development is that BFOA performs best in terms of electricity cost and carbon footprint due to its strong search capability while searching for optimal solutions. On the other hand, the BPSO algorithm outperforms in terms of PAR and delay (waiting time) due to its diverse population handling capability while finding the optimal solutions. Thus, the key operators of BFOA, i.e., chemotaxis, reproduction, and elimination-dispersal, are applied to the gbest optimal values returned from the BPSO algorithm. The velocity updating formula of the BPSO algorithm is shown in Algorithm 1. The chemotaxes step of BFOA is conducted as shown in Algorithm 2. With this hybridization, we obtained our objectives that are the cost of electricity minimization, PAR alleviation, and carbon footprint mitigation while preserving relative user comfort. The purpose is to ensure power grid reliability and sustainability. For instance, our proposed algorithm HBFPSO comprises two phases: In the first phase, this algorithm follows the steps of BPSO algorithm, whereas in the second phase the steps of BFOA are applied to the best-returned results. For example if we take pattern of seven peak hours, the results returned after the completion of BPSO phase is [0 0 0 1 1 1 1] here six appliances are ON, if this result is passed to the key steps of BFOA the results returned is [1 0 0 0 0 0 1] here 4 appliances are in ON status. Thus our proposed algorithm shifted the appliances from on-peak hours to off-peak hours. Thus, this behavior is also presented in Figure 21. The step by step implementation procedure of the proposed algorithm HBFPSO is illustrated in Fig. 9. The complete implementation of the proposed model for efficient DSM of residential, commercial, and industrial service areas is shown in Algorithm 3.
Algorithm 1: Binary Particle Swarm Optimization Algorithm: Velocity Updating

begin
  Updating velocity
  Initialize velocity by using 12
  for $j = 1 : \text{swarm}$ do
    for $i = 1 : m$ do
      $v_{\text{new}} = w \times v_{\text{old}} + c_1 \times \text{rand}(1) \times (p_{\text{best}} - x_{\text{old}}) + c_2 \times \text{rand}(1) \times (g_{\text{best}} - x_{\text{old}})$
      if $v_{\text{new}} < V_{\text{max}} \&\& v_{\text{new}} > V_{\text{min}}$ then
        $v_{\text{new}}(i, j) = v_{\text{new}}(i, j)$
      else
        if $v_{\text{new}} < V_{\text{min}}$ then
          $v_{\text{new}} = V_{\text{min}}$
        else
          if $v_{\text{new}} > V_{\text{max}}$ then
            $v_{\text{new}} = V_{\text{max}}$
          end
        end
      end
    end
  end
end

Algorithm 2: Bacterial Foraging Optimization Algorithm: Chemotaxis Steps

begin
  Chemotaxis
  for $j = 1 : N_c$ do
    for $i = 1 : N_p$ do
      Determine the initial position
      $\theta(i, :) = \theta(i, :) + C_{i1} \times \sqrt{1 \div T_{i1}}$
      for $d = 1 : (m - 1)$ do
        Compute fitness: $J = \text{Fit}_\text{function}(i)$
      end
      $s = 0$ while $s < N_s$
      swimming loop
      if $J(i) = J_{\text{last}}(i)$ then
        evaluating fitness
      end
      $J(i) = J(i)$ Determine new position $\theta(i, :)$
      for $d = 1 : (m - 1)$ do
        Determine fitness function
        $\text{Fit}_\text{function}(i)$
      end
    end
  end
end

FIGURE 9. The implementation procedure of the proposed HBFPSO algorithm for DSM of residential sector, commercial sector, and industrial sector.

To evaluate the efficacy of the proposed and existing algorithms test functions like Schaffer function, Weierstrass function, and Non-continuous Rastrigin’s function [54] are employed in simulations, which are listed in the Table 8.

All the aforementioned heuristic algorithms are capable to produce good solutions in solving non-linear problems where conventional algorithms normally fail. Although, their implementation complexity and slow convergence has limited wide range applicability. In this regard, HBFPSO algorithm is proposed, which successfully combat the limitations of existing algorithms like GA, BFOA, BPSO, and GBPSO. The efficacy of proposed HBFPSO algorithm is tested on three benchmark test functions, including Schaffer, Weierstrass, and Non-continuous Rastrigin’s, and the obtained results presented in Figure 10. The proposed and existing algorithms are compiled for 20 iterations mean and standard deviation values are recorded using Schaffer, Weierstrass, and Non-continuous Rastrigin’s benchmark functions as listed in Table 9. The results show that our proposed algorithm is superior as compared to existing algorithms.

VI. SIMULATION RESULTS AND DISCUSSIONS

In this section, we present and discuss the results of our simulations where we compare the performance of our proposed algorithm HBFPSO-based EMC with four other heuristic algorithms, i.e., BFOA, GA, BPSO, and GBPSO-based
EMCs in terms of cost, PAR, and CO₂ emissions while preserving user comfort. We compare the performance of these algorithms under three different scenarios, where each scenario is characterized by different price-based DR programs for residential, commercial, and industrial sectors. A load of demand-side like residential, commercial, and industrial service areas is taken DISCO MISO under FERC [55]. The MLP-based forecast engine is empowered via training with historical data to forecast the future load in order to ensure efficient DSM. The MLP-based forecasted of residential, commercial, and industrial service areas is depicted in Fig. 11. We divided this work into three scenarios on the basis of different price-based DR programs offered by DISCO. In the first, second, and third scenarios DA, CPP and ToU price-based DR programs are used, respectively. The MLP-based forecasted of residential, commercial, and industrial service areas as depicted in Fig. 11 is utilized by HBFPPO algorithm-based EMC under each of the three scenarios to ensure efficient DSM. The detailed discussion is as follows:

A. SCENARIO 1: MLP-BASED FORECASTING WITH DAY AHEAD PRICE-BASED DR PROGRAM

In this scenario, we consider the DA price-based DR program, which is taken from DISCO MISO under FERC [55]. The MLP-based forecast engine is empowered by supervised learning to forecast price-based DR program DA offered

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### TABLE 8. Benchmark test functions for evaluation of the proposed and existing algorithms.

| Test functions               | Search range   | Initial range   | Formulae                                                                 |
|------------------------------|----------------|-----------------|--------------------------------------------------------------------------|
| Schaffer                     | [-100, 100]    | [-100, 50]      |  
|                              |                |                | \( f(x) = 0.5 + \frac{\sin^2 \left( \sqrt{x_1^2 + x_2^2} \right) - 0.5}{(1 + 0.001(x_1^2 + x_2^2))^2} \) |
| Non-continuous Rastrigin     | [-5.12, 5.12]  | [-5.12, 2]      | \( \sum_{i=1}^{D} \left( y_i^2 - 10 \cos(2\pi y_i) + 10 \right) \) \begin{cases} x_i \text{ if } |x_i| < \frac{1}{2} \\ \text{round}(2x_i) \text{ if } |x_i| \geq \frac{1}{2} \end{cases} |
| Weierstrass                  | [-0.5, 0.5]    | [-0.5, 0.2]     | \( \sum_{i=1}^{D} \left( \sum_{k=0}^{\text{max}} \left[ a^2 \cos \left( 2\pi b^k (x_i + 0.5) \right) \right] \right) \\
|                              |                |                | \(-D \sum_{k=0}^{\text{max}} \left[ a^k \cos \left( 2\pi b^k 0.5 \right) \right] \right) \\
|                              |                |                | a = 0.5, b = 3, \text{max} = 20                                          |

### TABLE 9. Results of the proposed and existing algorithms for benchmark functions including schaffer, weierstrass, and non-continuous Rastrigin’s for 20 iterations.

| Optimization Techniques | Non-continuous Rastrigin | Schaffer Function | Weierstrass Function |
|-------------------------|--------------------------|-------------------|---------------------|
| BFOA Mean               | 0.165                    | 5.844             | 0.028               |
| STD.                    | 0.734                    | 3.536             | 0.006               |
| GA Mean                 | 0.945                    | 10.844            | 0.632               |
| STD.                    | 1.674                    | 9.032             | 1.865               |
| BPSO Mean               | 0.000578                 | 6.547             | 0.0096              |
| Std.                    | 0.000342                 | 3.093             | 0.0082              |
| GBPSO Mean              | 1.22E-11                 | 8.02E-02          | 7.02E-18            |
| STD.                    | 2.76E-13                 | 6.18E-02          | 1.04E-16            |
| HBFPPO Mean             | 4.76E-17                 | 1.49E-03          | 1.18E-24            |
| STD.                    | 8.56E-16                 | 7.35E-04          | 1.87E-23            |
Algorithm 3: The Proposed HBFPSSO Algorithm-Based EMC Employed for DSM of Residential Sector, Commercial Sector, and Industrial Sector via Load Scheduling Under Forecasted Price-Based DR Programs

Inputs: Net operation time for each category of residential sector, commercial sector, and industrial sector loads, Power rating, Forecasted offered price, Forecasted demand side load, Time slots for each load, Location for each load in time slot;

Initialize all parameters \( V_{\text{max}}, V_{\text{min}}, \text{iter}, N_r, N_c, N_p, \text{maxgen}, \text{maxpop} \)

for hop = 1:24 do
    Initialize velocity by using (43);
    for j = 1:swarm do
        Update velocity by using (44);
        if \( v_{\text{new}} < V_{\text{min}} \) then
            \( v_{\text{new}} (i, j) = v_{\text{new}} (i, j) \)
        else
            \( v_{\text{new}} = V_{\text{min}} \)
        end
        if \( v_{\text{new}} > V_{\text{max}} \) then
            \( v_{\text{new}} = V_{\text{max}} \)
        else
            \( v_{\text{new}} (i, j) = v_{\text{new}} (i, j) \)
        end
    end
    \( \text{popnew} = \text{X1} \)
    BFOA steps follows after new population;
    \( \text{X1} = \text{rand}(N_p, D) \)
    for j = 1:Np do
        for i = 1:D do
            if \( \text{X1}(j, i) > \text{X}(j, i) \) then
                \( \text{X1}(j, i) = 1 \)
            else
                \( \text{X1}(j, i) = 0 \)
            end
        end
        Reproduction loop
        for k = 1:Nr do
            Chemotaxis loop
            for j = 1:Nc do
                Take chemotaxis step
                \( \text{gbest elimination dispersal; For cost Load = power*gbest begin} \)
                Scenario 1: MLP-based forecasted day-ahead price-based DR program
                Calculate cost using (33);
                For FRA scheduledload = power*gbest
                Calculate PAR using (35);
                For CO\(_2\) emission
                Calculate CO\(_2\) emission using (36);
                For user comfort
                Calculate delay or waiting using (37);
                end procedure
                \( \text{end} \)
                Scenario 2: MLP-based forecasted CPP price-based DR program
                Calculate cost using (33);
                For FRA scheduledload = power*gbest
                Calculate PAR using (35);
                For CO\(_2\) emission
                Calculate CO\(_2\) emission using (36);
                For user comfort
                Calculate delay or waiting using (37);
                end procedure
                \( \text{end} \)
                Scenario 3: MLP-based forecasted ToU price-based DR program
                Calculate cost using (33);
                For FRA scheduledload = power*gbest
                Calculate PAR using (35);
                For CO\(_2\) emission
                Calculate CO\(_2\) emission using (36);
                For user comfort
                Calculate delay or waiting using (37);
                end procedure
                \( \text{end} \)
            end
        end
    end
end

price, which is shown in Fig. 12. According to the forecasted DA offered price 1 − 8 and 16 − 21 are the off-peak hours, 9 − 15 are peak hours, whereas 22 − 24 are shoulder peak hours. The HBFPSSO algorithm-based EMC use the forecasted demand side load and forecasted DA offered price in order to shift the load from on-peak hours to off-peak hours via load scheduling in order to ensure efficient DSM. The detail discussion is as follows:

1) DEMAND-SIDE LOAD PROFILES

Figure 13 shows the load profiles for the DA price-based DR program scenario. The unscheduled case where EMC is not employed, the energy consumption is high during 5 − 10, 14 − 17 and 18 − 21 hours compared to load scheduling.
where EMC is employed, which leads to higher energy consumption during peak hours that results in higher PAR and higher electricity costs. On the contrary, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO-based EMC for the residential sector is limited to 3.7kWh, 3.3kWh, 2.4kWh, 2kWh, and 2.9kWh, respectively. Whereas, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO for the commercial sector is limited to 3.9kWh, 3.6kWh, 2.4kWh, 2.1kWh and 2.5kWh, respectively. Similarly, for the industrial sector, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO is limited to 11.1kWh, 12.1kWh, 9.5kWh, 9kWh, and 9.3kWh, respectively. Thus, our proposed HBFPSO algorithm-based EMC has an optimal load profile as compared to the GA, BFOA, BPSO, and GBPSO algorithms-based EMC for the residential, commercial, and industrial sectors, respectively.

Based upon a detailed comparison as listed in Tables 10, 11, and 12; our proposed method gives best performance than other heuristic algorithm-based EMC algorithms in terms of PAR for all three sectors considered in this study, i.e., residential, commercial, and industrial, respectively.

2) Cost Profiles

Figure 14 shows the cost profiles for different algorithms across different sectors. For the residential sector, the daily cost

| Scheduling techniques | PAR (kWh) | Difference | Percentage decrements |
|-----------------------|-----------|------------|-----------------------|
| Unscheduled           | 4.5757    |            |                       |
| GA                    | 3.6196    | 0.9561     | 23.3%                 |
| BFOA                  | 3.4122    | 1.1635     | 29.13%                |
| BPSO                  | 2.7074    | 1.8683     | 51.30%                |
| HBFPSO                | 2.4367    | 2.139      | 61.00%                |
| GBPSO                 | 2.6825    | 1.8932     | 52.16%                |

TABLE 11. Comparison of PAR for commercial sector under DA price-based DR program.

| Scheduling techniques | PAR (kWh) | Difference | Percentage decrements |
|-----------------------|-----------|------------|-----------------------|
| Unscheduled           | 4.0455    |            |                       |
| GA                    | 2.9245    | 1.121      | 32.16%                |
| BFOA                  | 3.684    | 0.3651     | 9.45%                 |
| BPSO                  | 2.3492    | 1.6963     | 53.05%                |
| HBFPSO                | 2.1558    | 1.8897     | 60.94%                |
| GBPSO                 | 2.2764    | 1.7691     | 55.96%                |
FIGURE 13. Comparison daily demand-side energy consumption profiles of the proposed and existing algorithm under DA price-based DR program: (a) Residential, (b) Commercial, (c) Industrial.

3) CO$_2$ EMISSIONS

Figure 15 shows the hourly CO$_2$ emissions for residential, commercial, and industrial sectors. It can be observed that the proposed HBFPSO algorithm results in the least amount of CO$_2$ emissions during 19, 12 and 21 hours for the residential sector. For commercial and industrial sectors, it results in the least amount of emissions during 10, 16, 19, and 14, 16 hours, respectively, which are the shoulder peak and peak hours. GA is the least effective in reducing carbon emissions compared to the other heuristic algorithms, i.e., BPSO, BFOA and GBPSO.

TABLE 12. Comparison of PAR for industrial sector under DA price-based DR program.

| Scheduling techniques | PAR     | Difference | Percentage decrements |
|-----------------------|---------|------------|-----------------------|
| Unscheduled           | 3.7775  |            |                       |
| GA                    | 2.3002  | 1.4773     | 48.61%                |
| BFOA                  | 2.8911  | 0.8864     | 26.58%                |
| BPSO                  | 1.8397  | 1.9378     | 68.99%                |
| HBFPSO                | 1.6564  | 2.1211     | 78.06%                |
| GBPSO                 | 1.8198  | 1.9577     | 69.99%                |

TABLE 13. Comparison of cost for residential sector under DA price-based DR program.

| Scheduling techniques | Cost      | Difference | Percentage decrements |
|-----------------------|-----------|------------|-----------------------|
| Unscheduled           | 395.5950  |            |                       |
| GA                    | 388.1830  | 7.412      | 1.89%                 |
| BFOA                  | 371.6105  | 23.9845    | 6.25%                 |
| BPSO                  | 362.1000  | 33.495     | 8.84%                 |
| HBFPSO                | 339.8970  | 55.698     | 15.14%                |
| GBPSO                 | 354.9574  | 40.9376    | 10.27%                |

TABLE 14. Comparison of cost for commercial sector under DA price-based DR program.

| Scheduling techniques | Cost      | Difference | Percentage decrements |
|-----------------------|-----------|------------|-----------------------|
| Unscheduled           | 458.8950  |            |                       |
| GA                    | 458.6925  | 0.2025     | 0.044%                |
| BFOA                  | 450.0620  | 8.833      | 1.94%                 |
| BPSO                  | 432.0350  | 26.86      | 6.02%                 |
| HBFPSO                | 409.7625  | 49.1325    | 11.31%                |
| GBPSO                 | 429.9050  | 28.99      | 6.52%                 |
GBPSO, which fair slightly better. HBFPSSO reduce carbon emission approximately 52.86%, 38.18%, and 25.54% for residential, commercial, and industrial sector, respectively, which is far better than other algorithms. On the other hand, GBPSO shows 64.54% reduction of carbon emission for industrial sector.

4) DELAY TIME USER COMFORT

Table 16 shows the time delay for each load category, i.e., portable un-interruptible and consistent load appliances in commercial sector. Similarly, Table 18 shows the time delay for each load category, i.e., portable interruptible and consistent load appliances in the industrial sector.

**TABLE 15.** Comparison of cost for industrial sector under DA price-based DR program.

| Scheduling techniques | Cost   | Difference | Percentage decrements |
|------------------------|--------|------------|-----------------------|
| Unscheduled            | 1342.8 |            |                       |
| GA                     | 1332.7 | 10.1       | 0.75%                 |
| BFOA                   | 1334.2 | 8.6        | 0.64%                 |
| BPSO                   | 1258.5 | 84.3       | 6.48%                 |
| HBFPSSO                | 1214.6 | 128.2      | 10.02%                |
| GBPSO                  | 1252.4 | 90.4       | 6.96%                 |

**TABLE 16.** Comparison of user comfort in terms of delay time for residential sector under DA price-based DR program.

| Scheduling technique | Portable interruptible load | Portable un-interruptible load | Consistent load |
|----------------------|------------------------------|--------------------------------|-----------------|
| GA                   | 2.2092                       | 5.1667                         | 0.6541          |
| BFOA                 | 1.3742                       | 1.0889                         | 0.3185          |
| BPSO                 | 1.6245                       | 1.6333                         | 0.1662          |
| HBFPSSO              | 2.5350                       | 2.6417                         | 4.6111          |
| GBPSO                | 1.6645                       | 1.0889                         | 0.1772          |

**TABLE 17.** Comparison of user comfort in terms of delay time for commercial sector under DA price-based DR program.

| Scheduling techniques | Portable interruptible load | Consistent load |
|-----------------------|------------------------------|-----------------|
| GA                    | 2.7770                       | 0.3523          |
| BFOA                  | 0.7675                       | 0.2349          |
| BPSO                  | 1.7626                       | 0.1041          |
| HBFPSSO               | 2.2321                       | 5.5000          |
| GBPSO                 | 1.9269                       | 0.1328          |

**TABLE 18.** Comparison of user comfort in terms of delay time for industrial sector under DA price-based DR program.

| Scheduling techniques | Portable interruptible load | Consistent load |
|-----------------------|------------------------------|-----------------|
| GA                    | 1.6458                       | 0.7177          |
| BFOA                  | 0.2131                       | 1.5751          |
| BPSO                  | 0.9101                       | 0.3807          |
| HBFPSSO               | 1.7083                       | 4.1597          |
| GBPSO                 | 0.7287                       | 0.3263          |
B. SCENARIO 2: MLP-BASED FORECASTED CPP DR PROGRAM

In this scenario, we consider the CPO price-based DR program, which is taken from DISCO MISO under FERC [55]. The MLP-based forecast engine is empowered by supervised learning to forecast price-based DR program offered critical peak price (CPP), which is shown in Fig. 12. According to the forecasted offered CPP 1 – 8 and 23 – 24 are off-peak hours, 8 – 14 and 17 – 23 are shoulder peak hours, and 14 – 17 are peak hours. The HBFPSo algorithm-based EMC use the forecasted demand side load and forecasted offered CPP to shift the load from on-peak hours to off-peak hours via load scheduling in order to ensure efficient DSM. The detail discussion is as follows:

1) LOAD PROFILES

Figure 17 shows the load profiles for this scenario. The scheduled energy consumption of GA, BFOA, BPSO, HBFPSo, and GBPSO for the residential sector is limited to 3.5 kWh, 3.7 kWh, 2.6 kWh, 2.4 kWh, and 2.5 kWh, respectively. Whereas, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSo, and GBPSO for the commercial sector is limited to 4 kWh, 3.3 kWh, 1.9 kWh, 1.65 kWh, and 2.3 kWh, respectively. Similarly, for the industrial sector, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSo, and GBPSO is limited to 11 kWh, 12.2 kWh, 10 kWh, 5.89 kWh, and 5.95 kWh, respectively.

Tables 19, 20 and 21 show that compared to the other heuristic algorithms, the proposed HBFPSo algorithm gives the best performance of scheduled load in terms of PAR for all three sectors considered in this study, i.e., residential, commercial, and industrial, respectively.

2) COST PROFILES

Figure 18 shows the cost profiles for different algorithms across different sectors. For the residential sector, the daily
FIGURE 17. Comparison daily demand-side energy consumption profiles of the proposed and existing algorithm under CPP price-based DR program: (a) Residential; (b) Commercial; (c) Industrial.

**TABLE 20.** Comparison of PAR for commercial sector under CPP DR program.

| Scheduling techniques | PAR | Difference | Percentage decrements |
|-----------------------|-----|------------|-----------------------|
| Unscheduled           | 3.35|            |                       |
| GA                    | 2.79| 0.56       | 18.24%                |
| BFOA                  | 2.75| 0.6        | 19.67%                |
| BPSO                  | 2.34| 1.01       | 35.50%                |
| HBFPSSO               | 2.14| 1.21       | 44.08%                |
| GBPSO                 | 2.33| 1.02       | 35.91%                |

**TABLE 21.** Comparison of PAR for industrial sector under CPP DR program.

| Scheduling techniques | PAR | Difference | Percentage decrements |
|-----------------------|-----|------------|-----------------------|
| Unscheduled           | 3.77|            |                       |
| GA                    | 2.92| 0.85       | 25.41%                |
| BFOA                  | 2.07| 1.7        | 58.21%                |
| BPSO                  | 1.84| 1.93       | 68.80%                |
| HBFPSSO               | 1.66| 2.11       | 77.71%                |
| GBPSO                 | 1.79| 1.98       | 71.22%                |

The percentage decrease in the cost of electricity achieved by different algorithms for residential, commercial, and industrial sectors is given in Tables 22, 23 and 24, respectively.

**TABLE 22.** Comparison of cost of the proposed and existing algorithms under CPP DR program for residential sector.

| Scheduling techniques | Cost  | Difference | Percentage decrements |
|-----------------------|-------|------------|-----------------------|
| Unscheduled           | 750.9 |            |                       |
| GA                    | 656.99| 93.91      | 13.35%                |
| BFOA                  | 556.9 | 194        | 29.6%                 |
| BPSO                  | 408   | 342.9      | 59.17%                |
| HBFPSSO               | 280.8 | 470.1      | 62.60%                |
| GBPSO                 | 400.84| 350.06     | 46.6%                 |

**TABLE 23.** Comparison of cost of the proposed and existing algorithms under CPP DR program for commercial sector.

| Scheduling techniques | Cost  | Difference | Percentage decrements |
|-----------------------|-------|------------|-----------------------|
| Unscheduled           | 801.5 |            |                       |
| GA                    | 774.5 | 27         | 3.42%                 |
| BFOA                  | 739   | 62.5       | 8.11%                 |
| BPSO                  | 485.6 | 315.9      | 49.08%                |
| HBFPSSO               | 280.8 | 772.7      | 64.9%                 |
| GBPSO                 | 485.2 | 316.3      | 49.16%                |

3) **CO$_2$ EMISSIONS**

Figure 19 shows the hourly CO$_2$ emissions for residential, commercial, and industrial sectors. It can be observed that the
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FIGURE 18. Comparison of hourly cost of the proposed and existing algorithms under CPP DR program: (a) Residential, (b) Commercial, (c) Industrial.

proposed HBFPso algorithm results in the least amount of CO\textsubscript{2} emissions during 18, 22, and 23 hour for all three sectors. The GBPSO algorithm is effective in reducing emissions during peak hours which are approximately 22.77\%, 52.43\%, and 78.5\% for residential, commercial, and industrial, respectively., whereas BPSO and GA are more effective in 18 – 24 hours. The BFOA algorithm is the most effective in 17 – 24 hours as compared to the other heuristic algorithms. HBFPso shows 20.63\% in reduction of carbon emission for residential sector.

4) DELAY TIME USER COMFORT

Table 25 shows the time delay for each load category, i.e., portable interruptible, portable un-interruptible, and consistent load appliances in the residential sector.

TABLE 25. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under CPP DR program for residential sector.

| Scheduling technique | Portable interruptible load | Portable un-interruptible load | Consistent load |
|----------------------|-----------------------------|--------------------------------|-----------------|
| GA                   | 2.58                        | 5.25                           | 0.56            |
| BFOA                 | 1.35                        | 1.8                            | 0.58            |
| BPSO                 | 2.3                         | 1.62                           | 0.25            |
| HBFPso               | 2.2                         | 1.95                           | 4.56            |
| GBPSO                | 2.32                        | 1.19                           | 0.23            |

Whereas, Table 26 shows the time delay for each load category, i.e., portable un-interruptible and consistent load appliances in commercial sector. Similarly, Table 27 shows the time delay for each load category, i.e., portable interruptible and consistent load appliances in the industrial sector.

TABLE 26. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under CPP DR program for commercial sector.

| Scheduling technique | Portable un-interruptible load | Consistent load |
|----------------------|-------------------------------|-----------------|
| GA                   | 2.92                          | 0.25            |
| BFOA                 | 1.2                           | 0.18            |
| BPSO                 | 0.56                          | 0.08            |
| HBFPso               | 2.33                          | 5.56            |
| GBPSO                | 0.65                          | 0.23            |

4) DELAY TIME USER COMFORT

Table 25 shows the time delay for each load category, i.e., portable interruptible, portable un-interruptible, and consistent load appliances in the residential sector.

TABLE 25. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under CPP DR program for residential sector.

| Scheduling technique | Portable interruptible load | Portable un-interruptible load | Consistent load |
|----------------------|-----------------------------|--------------------------------|-----------------|
| GA                   | 2.58                        | 5.25                           | 0.56            |
| BFOA                 | 1.35                        | 1.8                            | 0.58            |
| BPSO                 | 2.3                         | 1.62                           | 0.25            |
| HBFPso               | 2.2                         | 1.95                           | 4.56            |
| GBPSO                | 2.32                        | 1.19                           | 0.23            |

Whereas, Table 26 shows the time delay for each load category, i.e., portable un-interruptible and consistent load appliances in commercial sector. Similarly, Table 27 shows the time delay for each load category, i.e., portable interruptible and consistent load appliances in the industrial sector.

C. SCENARIO 3: MLP-BASED FORECASTED ToU PRICE-BASED DR PROGRAMS

In this scenario, we consider the ToU price-based DR program, which is taken from DISCO MISO under FERC [55]. The MLP-based forecast engine is empowered by supervised learning to forecast ToU price-based DR program offered
price, which is shown in Fig. 20. According to the forecasted ToU price-based DR program 1 – 8 and 22 – 24 are off-peak hours, 9 – 13 and 17 – 21 are shoulder peak hours, and 14 – 16 are peak hours. The HBFPSO algorithm-based EMC use the forecasted demand side load and forecasted ToU price-based DR program to shift the load from on-peak hours to off-peak hours via load scheduling in order to ensure efficient DSM. The detail discussion is as follows:

1) LOAD PROFILES
Figure 21 shows the load profiles for this scenario. The scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO for the residential sector is limited to 3.4 kWh, 3.6 kWh, 2.6 kWh, 2.6 kWh, and 2.4 kWh, respectively. Whereas, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO for the commercial sector is limited to 4 kWh, 3.9 kWh, 2.3 kWh, 2 kWh, and 2.5 kWh, respectively. Similarly, for the industrial sector, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO is limited to 11 kWh, 12 kWh, 9 kWh, 5.8 kWh, and 5.88 kWh, respectively.

Tables 28, 29 and 30 show that compared to the other heuristic algorithms, the proposed HBFPSO algorithm gives the best performance of scheduled load in terms of PAR for all three sectors considered in this study.

2) COST PROFILES
Figure 22 shows the cost profiles for different algorithms across different sectors. For the residential sector, the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is $8.7, $7.7, $8.2, $7.1, $5, and $6, respectively. Whereas, for
FIGURE 21. Comparison of demand-side energy consumption profiles of the proposed and existing algorithms under ToU price-based DR program: (a) Residential, (b) Commercial, (c) Industrial.

commercial sector the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSEO, and GBPSO is $9.6, $9, $9.5, $8.5, $8.2, and $8.4, respectively. Similarly, for the industrial sector, the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSEO, and GBPSO is $28.1, $26.7, $27.2, $24.9, $24.4, and $24.8, respectively.

The percentage decrease in the cost of electricity achieved by different algorithms for residential, commercial, and industrial sectors is given in Tables 31, 32 and 33, respectively.

3) CO₂ EMISSIONS

Figure 23 shows the hourly CO₂ emissions for residential, commercial, and industrial sectors. It can be observed that all the algorithms show similar results in reducing CO₂ emissions. Our proposed HBFPSEO shows better result in term of

TABLE 28. Comparison of PAR of the proposed and existing algorithms under ToU price-based DR program for residential sector.

| Scheduling techniques | PAR | Difference | Percentage decrements |
|-----------------------|-----|------------|-----------------------|
| Unscheduled           | 4.57|            |                        |
| GA                    | 3.52| 1.05       | 25.95%                |
| BFOA                  | 4.18| 0.39       | 8.91%                 |
| BPSO                  | 2.57| 2          | 56.02%                |
| HBFPSEO               | 2.36| 2.21       | 63.78%                |
| GBPSO                 | 2.52| 2.05       | 57.82%                |

TABLE 29. Comparison of PAR of the proposed and existing algorithms under ToU price-based DR program for commercial sector.

| Scheduling techniques | PAR | Difference | Percentage decrements |
|-----------------------|-----|------------|-----------------------|
| Unscheduled           | 3.35|            |                        |
| GA                    | 3.21| 0.14       | 4.26%                 |
| BFOA                  | 2.55| 0.8        | 27.1%                 |
| BPSO                  | 2.37| 0.98       | 34.26%                |
| HBFPSEO               | 2.07| 1.28       | 47.23%                |
| GBPSO                 | 2.24| 1.11       | 39.71%                |

TABLE 30. Comparison of PAR of the proposed and existing algorithms under ToU price-based DR program for industrial sector.

| Scheduling techniques | PAR | Difference | Percentage decrements |
|-----------------------|-----|------------|-----------------------|
| Unscheduled           | 3.77|            |                        |
| GA                    | 3.27| 0.5        | 14.20%                |
| BFOA                  | 2.39| 1.38       | 44.80%                |
| BPSO                  | 1.83| 1.94       | 69.28%                |
| HBFPSEO               | 1.65| 2.12       | 78.22%                |
| GBPSO                 | 1.77| 2          | 72.20%                |
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FIGURE 22. Comparison of hourly cost of the proposed and existing algorithms under ToU price-based DR program: (a) Residential, (b) Commercial, and (c) Industrial.

reduction of CO\textsubscript{2} emission. It reduce 23.02%, 15.58%, and 6.297\% for residential, commercial, and industrial sectors, respectively. While GBPSO and BPSO recuce carbon emission 69.86\% and 67.23\% for industrial sector respectively.

4) DELAY TIME USER COMFORT

Table 34 shows the time delay for each load category, i.e., portable interruptible, portable un-interruptible, and consistent load appliances in residential sector.

Whereas, Table 35 shows the time delay for each load category, i.e., portable un-interruptible and consistent load appliances in commercial sector. Similarly, Table 36 shows the time delay for each load category, i.e., portable interruptible and consistent load appliances in the industrial sector.
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VII. CONCLUSION

The increasing power demand due to population growth, industrialization, and economic development had augmented DISCO’s stress. To meet this unfettered rise in electricity demand, an intelligent framework through optimization and artificial intelligence is introduced that employs HBFPSO algorithm-based EMC for efficient DSM under forecasted price-based DR programs. The HBFPSO algorithm-based EMC schedule the operation of appliances under three different price-based DR programs: DA, CPP, and ToU, aiming to minimize electricity cost, PAR, user discomfort, and carbon emissions. The proposed methodology is evaluated for three demand-side sectors under three price-based DR programs such as DA, CPP, and ToU. However, it has the potential to be applied for DSM of transportation and agriculture sectors with other price-based DR programs like RTP, IBR, and CPR, or even other incentive-based DR programs. Using the proposed intelligent DSM framework, the DISCO can solve the lack of electricity during on-peak hours either by shifting the loads in time, increase the loads or even fill up the valley when electricity production is predominately increasing over the consumption. The proposed framework is validated by comparing it to five benchmark heuristic algorithms-based frameworks like GA, BFOA, BPSO, and GBPSO in terms of four performance metrics, i.e., cost of electricity, curtailment of PAR, reduction in users’ discomfort, and mitigation of carbon emissions. The proposed scheme has reduced electricity cost, user discomfort, PAR, and CO₂ emission for the residential sector by 15.14%, 4.6%, 61.6%, and 52.86% in scenario 1, 62.60%, 4.56%, 60.77%, and 27.77% in scenario 2, and 26.03%, 4.54%, 63.78%, and 23.02% in scenario 3, as compared to without an EMC. Similarly, for commercial sector the proposed HBFPSO algorithm reduces electricity cost, user discomfort, PAR, and CO₂ emission by 11.31%, 5.5%, 60.9%, and 38.18% in scenario 1, 64.9%, 5.56%, 44.08%, and 58.8% in scenario 2, 15.31%, 5.26%, 78.22%, and 15.58% in scenario 3. Likewise, the proposed algorithm also has superior performance for the industrial sector for all the three scenarios. In future, this work can be extended into diverse directions, which are elaborated as follows:

1) The DSM via scheduling can be performed through the coordination among different sectors in the presence of power grid, renewable energy, energy storage systems, and electric vehicles by embedding sensors and the internet of things (IoT) modules on each participant. The EMC could be made intelligent and smart by incorporating sensing, communication, and the IoT modules on the traditional EMC to handle such a coordinated environment. Furthermore, for this coordinated environment, net metering is required where consumers would become prosumers. The prosumers can generate

| Scheduling techniques | Portable interruptible load | Consistent load |
|-----------------------|-----------------------------|------------------|
| GA                    | 1.95                        | 0.68             |
| BFOA                  | 0.3                         | 1.41             |
| BPSO                  | 0.65                        | 0.5              |
| HBFPSO                | 1.7                         | 4.19             |
| GBPSO                 | 0.5                         | 0.3              |

TABLE 36. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under ToU price-based DR program for industrial sector.

FIGURE 23. Comparison of CO₂ emissions of the proposed and existing algorithms under ToU price-based DR program: (a) Residential, (b) Commercial, (c) Industrial.
renewable energy and store it into the energy storage systems and electric vehicles that have storage batteries. The prosumers store their generated energy in storage systems, sell to the other consumers, and back to the power grid to ensure reliable, stable, sustainable, and economical power grid operation. The prosumers enabled with intelligent and smart EMC and net metering features can actively participate in regulated energy markets with price-based DR programs and incentive-based DR to facilitate both the power grid and consumers.

2) This work can be extended to fog and cloud-based DSM employing various DR programs to achieve the desired balance between demand and supply.

3) This work can also be extended by engaging some advanced, intelligent, and loads that have time as well as power flexibility for efficient energy management. Such types of loads will provide more opportunities for EMC to engage them in DSM to provide economical and sustainable solutions.

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