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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_2) emissions in a controlled manner. Building an optimization framework that will minimize cost, peak demand, waiting time, and CO_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_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_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_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_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_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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NOMENCLATURE

N	Total number of homes
m	Total number of appliances
A	Set of appliances
τ	Time interval for each appliance
T	Total time interval
A_{pi}	Set of portable interruptible appliances
A_{pni}	Set of portable un-interruptible appliances
A_c	Set of consistent appliances
λ	Power rating
$\rho(\tau)$	Price signal
ε	Total power usage per day for each category of load
σ^{τ}	Cost per hour
ς^{total}	Cost per day
γ	Total load consumed
N_E	Power usage for each appliances
Ne	Number of elimination steps
Nr	Number of reproduction steps
Nc	Number of chemotaxis steps
Ns	Number of swimming steps
Np	Number of population steps
Ci	Step size
$vmax$	Upper velocity limit in BPSO
$vmin$	lower velocity limit in BPSO
Pc	Probability of crossover
wi	Initial weight constant
AMI	Advance metering infrastructure
BPSO	Binary particle swarm optimization
BFOA	Bacterial foraging optimization algorithm
CPP	Critical peak pricing
CO_2	Carbon emission
DR	Demand response
DSM	Demand side management
EMC	Energy management controller
GA	Genetic algorithm
gbest	Global best
HGBPSO	Hybrid of GA and BPSO algorithm
HBFPSO	Hybrid of BFOA and BPSO algorithm
HEMS	Home energy management system
HESS	Hybrid electrical storage systems
ICTs	Information and communication technologies
IBR	Inclined block rate
NILM	Non-intrusive load monitoring
PAR	Peak to average ratio
Pbest	Personal best
RTP	Real time pricing
SG	Smart grid
ToU	Time of use
WLAN	Wireless local-area network
Pm	Probability of mutation
wf	Finial weight constant

I. INTRODUCTION

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]. In [4], an energy management framework is proposed for smart energy storage and scheduling schemes for appliances, which allows consumers to save on electricity costs in two ways. First, it enables them to schedule their power consumption during off-peak hours when prices are low. Second, during peak hours, when prices are high, consumers can meet their power requirements through their energy storage devices. Despite its obvious advantages, the resulting system is complex. For instance, in [5], 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.

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 household's energy resources are managed in such a way to maximize self-consumption and minimize consumption from the utility. In [9], the authors reduce the cost of electricity, consumer discomfort, and peak energy consumption by proposing a genetic binary particle swarm optimization (GBPSO) algorithm under a dynamic pricing model. The GBPSO performance is evaluated by comparing it with two heuristic optimization techniques, i.e., genetic algorithm (GA), and binary particle swarm optimization (BPSO) in terms of residential load management. In [10], a real-time price-based demand response (DR) program is proposed for residential load management using stochastic and robust optimization techniques, which are formulated as mixed-integer linear programming problems. In [11], the authors proposed bidirectional communication between the consumer and the grid 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 GBPSO, 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 customer 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 modified 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, CO_2 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]Opportunis-tic 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]Decomposi-tion 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 ACLPS	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
[43]Stochastic and robust optimization	minimizing electricity cost	Real-time-price-based DR program	PAR and user comfort are not considered
[44]Opportunis-tic 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] AMI 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	Decreases 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 layout, 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:

$$F(t) = \sum_{i=1}^{n} W_i f(y_i) + \sum_{j=1}^{m} \beta_j z_j, \tag{1}$$

where,

$$f(y_i) = \frac{1}{1 + \exp(-y_i)} \tag{2}$$

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, β_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:

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

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 epoches 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:

$$E = \frac{1}{N} \sum_{k=1}^{N} (A_k - F_k)^2, \tag{4}$$

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

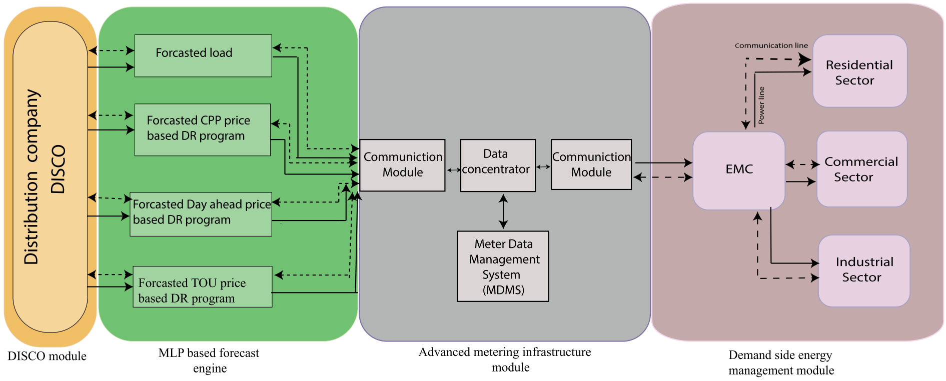


FIGURE 1. Schematic diagram of the proposed intelligent system model with a forecaster and advanced metering infrastructure frameworks for DSM in smart grid.

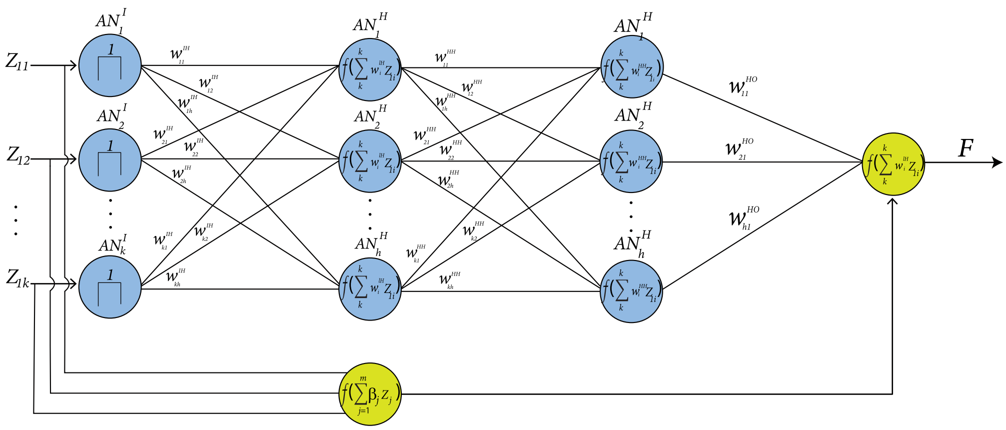


FIGURE 2. MLP-based forecast engine for demand side load forecasting and price-based DR program forecasting.

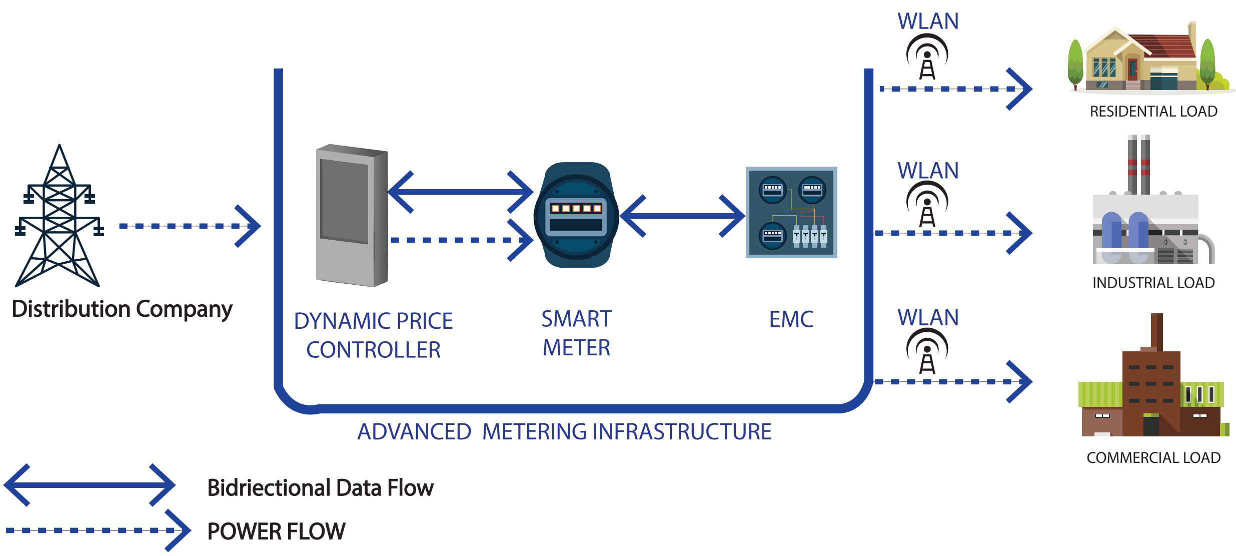


FIGURE 3. Advanced metering infrastructure framework connected with power company and consumers.

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 act 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, forecasted energy consumption pattern, available energy, as well as the residential, commercial, and industrial sector appliance parameters (power rating, operation time interval, status, priority) as inputs to solve DSM optimization problem. The DSM under price-based DR programs can be monitored and controlled for modification either by IDD device or by remote control units like mobile phones or tablets via the internet. The demand-side energy management architecture is depicted in Figure 4. The detailed description of the load of each service area that HBFPSO-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 $A_r = A_{pi} \cup A_{pni} \cup A_c$ represent a set of residential sector appliances, where A^r_{pi}, A^r_{pni}, and A^r_c 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 $T = \tau_1, \tau_2, \tau_3 \ldots\ldots\ldots \tau_{24}$.

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^r_{pi} be the set of portable interruptible appliances and $a^r_{pi} \in A^r_{pi}$ represent each appliance in the set with λ^r_{pi} as its power rating. The total energy consumption per day for the portable interruptible load ε^r_{pi} can be given by (5).

$$\varepsilon^r_{pi} = \sum_{a_{pi^r} \in A^r_{pi}} \left[\sum_{\tau=1}^{T} \lambda^r_{pi} \times \alpha(\tau) \right] \tag{5}$$

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

$$\varsigma^{total^r}_{pi} = \sum_{a_{pi^r} \in A^r_{pi}} \left[\sum_{\tau=1}^{T} \lambda^r_{pi} \times \rho(\tau) \times \alpha(\tau) \right], \tag{6}$$

Here, $\rho(\tau)$ represents the price signal, whereas, $\alpha(\tau) \in [0, 1]$ represents the state of an appliance, i.e., *ON or OFF*. Similarly, the cost of electricity consumed per hour by the interruptible residential applianceе is given in (7).

$$\sigma^{\tau^r}_{pi} = \sum_{a_{pi^r} \in A^r_{pi}} \left(\lambda^r_{pi} \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T \tag{7}$$

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

c: PORTABLE UN-INTERRUPTIBLE LOAD

The portable un-interruptible load includes appliances like washing machines and blenders. In such type of load, we assume that cannot be interrupted during operation but can be operated at any time. Let A_{pni} be the set of un-interruptible appliances, and let $a_{pni} \in A_{pni}$ represent each appliance in the set. Let λ^r_{pni} be the power rating of each appliance. The total energy consumption ε^r_{pni} for the portable un-interruptible load over a time period T is given by (8).

$$\varepsilon^r_{pni} = \sum_{a_{pni^r} \in A^r_{pni}} \left[\sum_{\tau=1}^{T} \lambda^r_{pni} \times \alpha(\tau) \right] \tag{8}$$

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

$$\varsigma^{total^r}_{pni} = \sum_{a_{pni^r} \in A^r_{pni}} \left[\sum_{\tau=1}^{T} \lambda^r_{pni} \times \rho(\tau) \times \alpha(\tau) \right] \tag{9}$$

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

$$\sigma^{\tau^r}_{pni} = \sum_{a_{pni^r} \in A^r_{pni}} \left(\lambda^r_{pni} \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T \tag{10}$$

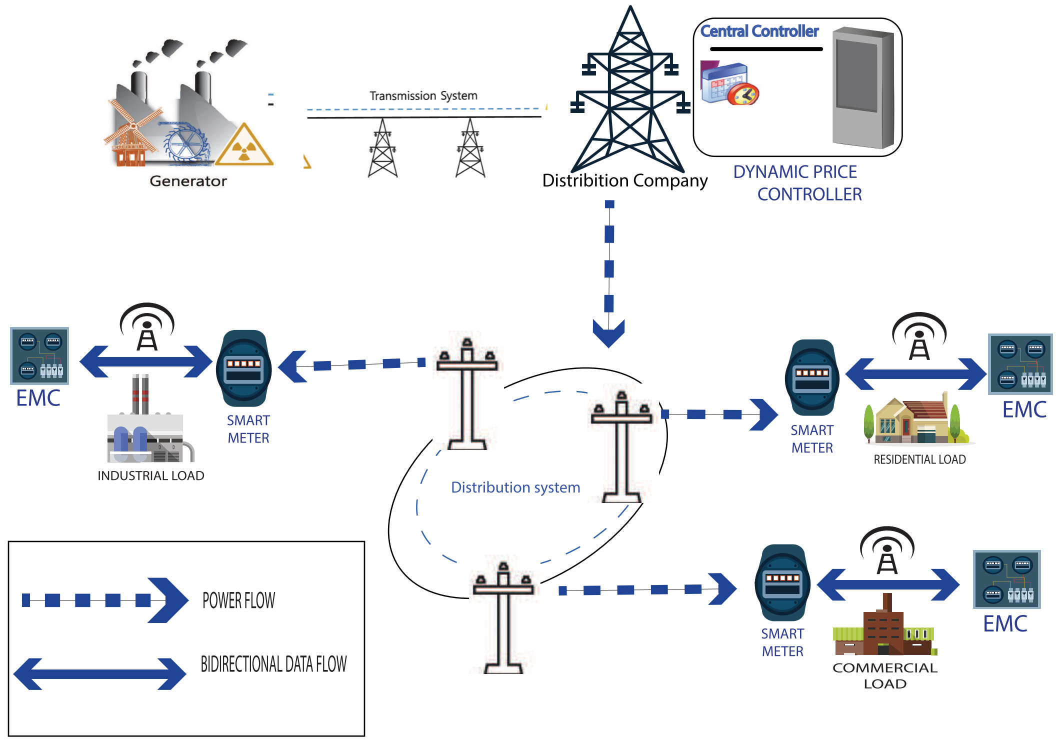


FIGURE 4. Architecture of demand side energy management module with EMC employed for residential, commercial, and industrial service areas.

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 λ_c. Then, the daily energy consumption ε_c^r for this set of appliances is given by (11).

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

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

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

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

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

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

$$\gamma_R = \varepsilon_{pi}^r + \varepsilon_{pni}^r + \varepsilon_c{}^r, \tag{14}$$

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).

$$N_r{}^r = \begin{bmatrix} \gamma R_{api}^{\tau 1} & \gamma R_{apni}^{\tau 1} & \gamma R_c^{\tau 1} \\ \gamma R_{api}^{\tau 2} & \gamma R_{apni}^{\tau 2} & \gamma R_c^{\tau 2} \\ \gamma R_{api}^{\tau 3} & \gamma R_{apni}^{\tau 3} & \gamma R_c^{\tau 3} \end{bmatrix} \tag{15}$$

TABLE 2. Description of appliances for residential sector.

Group	Appliances	Power rating (kW)	Daily usage (h)
Portable interruptible	Cooking range	0.40	4
	Personal computer	0.35	4
	Well pump	0.9	4
	Microwave	0.25	7
	Blender	0.30	4
Portable un-interruptible	Washing machine	0.50	2
	Iron	1.00	2
Consistent appliances	Water purifier	0.50	9
	Refrigerator	2.50	12
	Fan	0.5	8

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 $A_c = A_{pni} \cup A_c$ represent a set of appliances, where A^c_{pni} and A^c_c represent the portable un-interruptible and consistent appliances, respectively. This categorization is based on commerical consumers requirement over a 24h time horizon, complete horizon is defined as $T = \tau_1, \tau_2, \tau_3 \ldots\ldots\ldots \tau_{24}$.

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 catagory is assumed not to be interrupted during operation but can be operated at any time. Let A^c_{pni} be the set of un-interruptible appliances and let $a^c_{pni} \in A^c_{pni}$ represent an appliance in this set with a power rating λ^c_{pni}. The total daily energy consumption ε^c_{pni} for this set of appliances can be calculated using (16).

$$\varepsilon^c_{pni} = \sum_{a_{pni^c} \in A^c_{pni}} \left[\sum_{\tau=1}^{T} \lambda^c_{pni} \times \alpha(\tau) \right] \tag{16}$$

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

$$\varsigma^{total^c}_{pni} = \sum_{a_{pni^c} \in A^c_{pni}} \left[\sum_{\tau=1}^{T} \lambda^c_{pni} \times \rho(\tau) \times \alpha(\tau) \right], \tag{17}$$

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

$$\sigma^{\tau^c}_{pni} = \sum_{a_{pni^c} \in A^c_{pni}} \left(\lambda^c_{pni} \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1:T \tag{18}$$

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 λ^c_c. Then, the total daily energy consumption, ε^c_c, for this set of appliances can be calculated using (19).

$$\varepsilon_c{}^c = \sum_{a_{c^c} \in A_c{}^c} \left[\sum_{\tau=1}^{T} \lambda^c_c \times \alpha(\tau) \right] \tag{19}$$

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

$$\varsigma^{total^c}_c = \sum_{a_{c^c} \in A_c{}^c} \left[\sum_{\tau=1}^{T} \lambda_c{}^c \times \rho(\tau) \times \alpha(\tau) \right], \tag{20}$$

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

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

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

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

$$\gamma_C = \varepsilon^c_{pni} + \varepsilon_c{}^c, \tag{22}$$

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):

$$N_c = \begin{bmatrix} \gamma C^{\tau 1}_{apni} & \gamma C^{\tau 1}_c \\ \gamma C^{\tau 2}_{apni} & \gamma C^{\tau 2}_c \\ \gamma C^{\tau 3}_{apni} & \gamma C^{\tau 3}_c \end{bmatrix} \tag{23}$$

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 $A_i = A_{pi} \cup A_c$ represent a set of appliances, where A^i_{pi} 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 $T = \tau_1, \tau_2, \tau_3 \ldots\ldots\ldots \tau_{24}$.

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_{pi}^{i} be the set of portable interruptible appliances and $a_{pi}^{i} \in A_{pi}^{i}$ represent each appliance in the set with λ_{pi}^{i} as its power rating. The total energy consumption per day for the portable interruptible load ε_{pi}^{i} can be given by (24).

$$\varepsilon_{pi}^{i} = \sum_{a_{pi^i} \in A_{pi}^{i}} \left[\sum_{\tau=1}^{T} \lambda_{pi}^{i} \times \alpha(\tau) \right] \tag{24}$$

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

$$\varsigma_{pi}^{total^i} = \sum_{a_{pi^i} \in A_{pi}^{i}} \left[\sum_{\tau=1}^{T} \lambda_{pi}^{i} \times \rho(\tau) \times \alpha(\tau) \right], \tag{25}$$

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.

$$\sigma_{pi}^{\tau^i} = \sum_{a_{pi^i} \in A_{pi}^{i}} \left(\lambda_{pi}^{i} \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T \tag{26}$$

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_c^i denote the set of consistent load appliances and let $a_c^i \in A_c^i$ represent an individual appliance in this set with a power rating of λ_c^i. Then, the total daily energy consumption, ε_c^i, for this set of appliances can be calculated using (27).

$$\varepsilon_{c} = \sum_{a_{c^i} \in A_{c^i}} \left[\sum_{\tau=1}^{T} \lambda_{c}^{i} \times \alpha(\tau) \right] \tag{27}$$

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

$$\varsigma_{c}^{total^i} = \sum_{a_{c^i} \in A_{c^i}} \left[\sum_{\tau=1}^{T} \lambda_{c}{}^{i} \times \rho(\tau) \times \alpha(\tau) \right], \tag{28}$$

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

$$\sigma_{c}^{\tau^i} = \sum_{a_{c^i} \in A_{c^i}} \left(\lambda_{c}{}^{i} \times \rho(\tau) \times \alpha(\tau) \right) \quad \forall \tau = 1 : T \tag{29}$$

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

$$\gamma_{I} = \varepsilon_{pi}^{i} + \varepsilon_{c}{}^{i}, \tag{30}$$

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 HBFPSO 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),

$$N_i = \begin{bmatrix} \gamma I_{api}^{\tau 1} & \gamma I_{c}^{\tau 1} \\ \gamma I_{api}^{\tau 2} & \gamma I_{c}^{\tau 2} \\ \gamma I_{api}^{\tau 3} & \gamma I_{c}^{\tau 3} \end{bmatrix} \tag{31}$$

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 τ, 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.

$$\sigma_{total}^{\tau} = \sum_{a_i \in A_n} \gamma_{(\tau, a_i)} \times \rho(\tau) \quad \forall \tau = 1 : T \tag{32}$$

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).

$$\varsigma_{total} = \sum_{\tau=1}^{T} \left(\sum_{a_{i \in A_n}} (\gamma_{(\tau, a_i)} \times \rho(\tau)) \right) \tag{33}$$

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 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:

$$\min\left(\sum_{\tau=1}^{T}\left(\sum_{a_{i\in A_n}}(\gamma_{(\tau,a_i)}\times\rho(\tau))\right)+CO_2+Delay+PAR\right) \tag{34}$$

where,

$$PAR=\frac{\max_{\tau\in T}(\gamma_\tau)}{\frac{1}{T}\sum_{\tau=1}^{T}\gamma_\tau}\leqslant E_{\max} \tag{35}$$

$$CO_2^{Perhour}=(Avg/price^{(Perhour)})*1.37*30 \tag{36}$$

$$Delay=(sum(abs(tA1-tA2)))/sum(tA2) \tag{37}$$

where, $CO_2^{Perhour}$ represents carbon emissions, and (36) gives the hourly CO_2 emissions during the peak load hours when the diesel generators are turned-on to meet the additional load. The *Delay* denotes the waiting time that each appliance face before to start operation, and *PAR* is the peak to average ratio. The equation (35) is a ratio of peak load and average load, which enable us to identify whether the load in peak hour is high or low and (36) represents the amount of carbon footprint emitting when using electricity per hour. In (37) $tA1$ represents operation time-slots before scheduling and $tA2$ represents operation time-slots of an appliance after scheduling. The objective function is subjected to the following constraints. The constraint in (35) specifies that the average energy consumption is always less than E_{max}.

$$E_{min}\leqslant E\leqslant E_{max} \tag{38}$$

Here, it must be noted that $E_{max} = 1$ cannot be achieved because the peak and average loads cannot be the same. The value of E_{max} is carefully selected to meet the constraint in (38), which specifies the limits for the scheduling interval.

$$\gamma_\tau=\varepsilon_{pi}+\varepsilon_{pni}+\varepsilon_c \tag{39}$$

$$\gamma_\tau\left(KW_g\right) \tag{40}$$

Similarly, the constraint in (39) guarantees that the power consumption remains the same before and after scheduling. The equation (40) ensures that the total energy consumption must be lower than the capacity of the power grid. Further, equation (41) ensures that the length of operation of each appliance is not affected by scheduling.

$$\sum_{\tau=1}^{T}\gamma_\tau{}^{unsch}=\sum_{\tau=1}^{T}\gamma_\tau{}^{sch} \tag{41}$$

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 generates the initial population with completely random solutions. Random solutions are the ones having large diversity, which leads to generating optimal population. The second method generates 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 flow chart Fig. 5. The parameters used for this algorithm implementation are listed in Table 5.

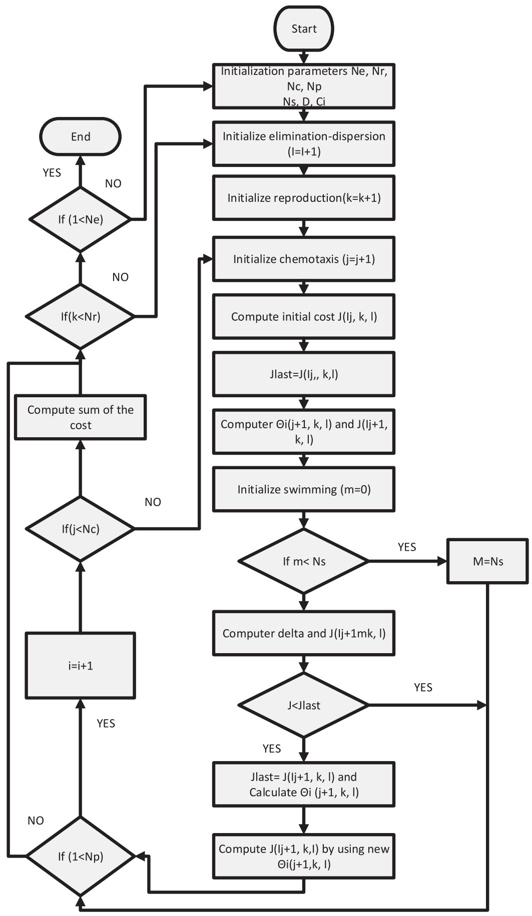


FIGURE 5. **The BFOA step by step procedure for the implementation in DSM environment.**

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
Θ	0.5
Ped	0.5
Maximum generation	14

B. GENETIC ALGORITHM

Genetic algorithm (GA) is another biologically inspired non-linear 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.

$$p_m = 1 - p_c \tag{42}$$

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
Pc	0.9
Pm	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

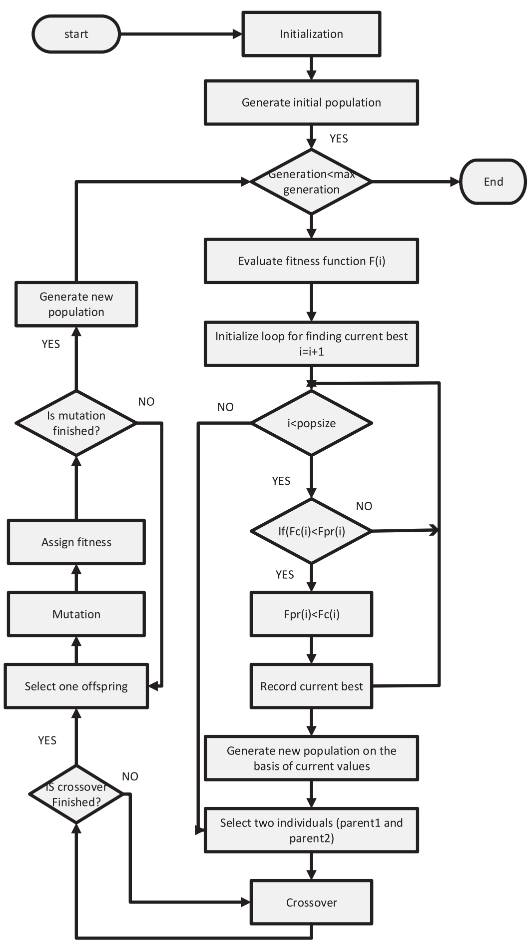


FIGURE 6. GA procedure for DSM under price-based DR programs.

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).

$$v_i = V_{\max} \times 2(rand(swarm, n) - 0.5) \tag{43}$$

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),

$$\begin{aligned} v[] = v[] + c1 \times rand() \times (pbest[] - present[]) \\ + c2 \times rand() \times (gbest[] - present[]), \end{aligned} \tag{44}$$

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

$$Present[] = Present[] + V[] \tag{45}$$

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

$$Sig(j, i) = \frac{1}{1 + e^{-vnew}} \tag{46}$$

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_i	2
w_f	0.4
v_{max}	4
v_{min}	-4

D. GENETIC BINARY PARTICLE SWARM OPTIMIZATION ALGORITHM

A hybrid algorithm genetic binary particle swarm optimization (GBPSO) is proposed, which combines the features of BPSO and GA. The GBPSO is illustrated in Fig. 8. It consists of two phases: In the first phase, the BPSO algorithm

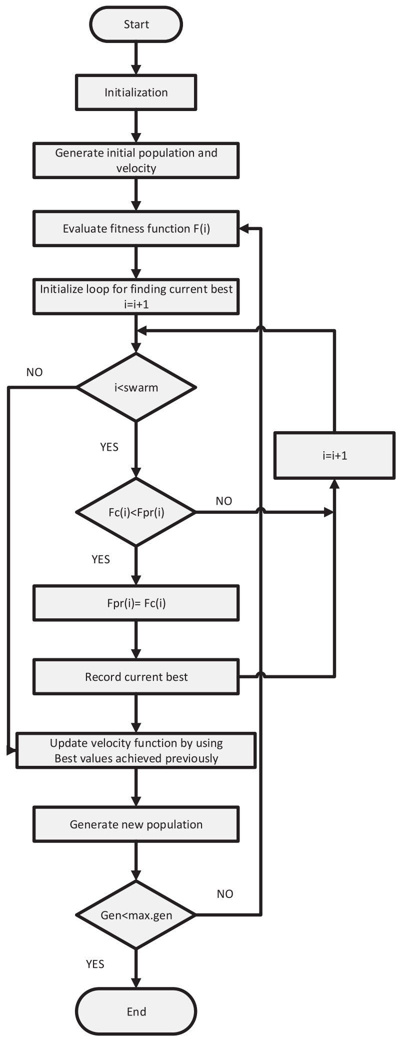


FIGURE 7. Flow chart of the BPSO algorithm for DSM under price-based DR programs.

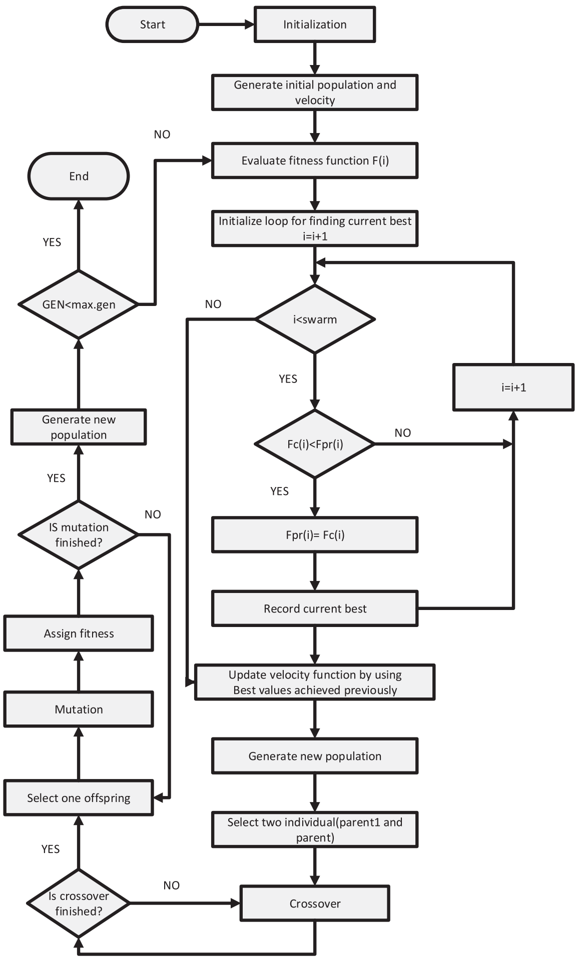


FIGURE 8. GBPSO step by step procedure for DSM under price-based DR programs.

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 form 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 $j = 1 : swarm$ **do**
    for $i = 1 : m$ **do**
      $v_{new} = w \times v_{old} + c_1 \times rand(1) \times (pbest - x_{old}) + c_2 \times rand(1) \times (gbest - x_{old})$
      if $v_{new} < Vmax \; \&\& \; v_{new} > Vmin$ **then**
        $v_{new}(i, j) = v_{new}(i, j)$
      else
      end
      if $v_{new} < Vmin$ **then**
        $v_{new} = Vmin$
      else
      end
      if $v_{new} > Vmax$ **then**
        $v_{new} = Vmax$
      end
      end
    end
    end
  end
end

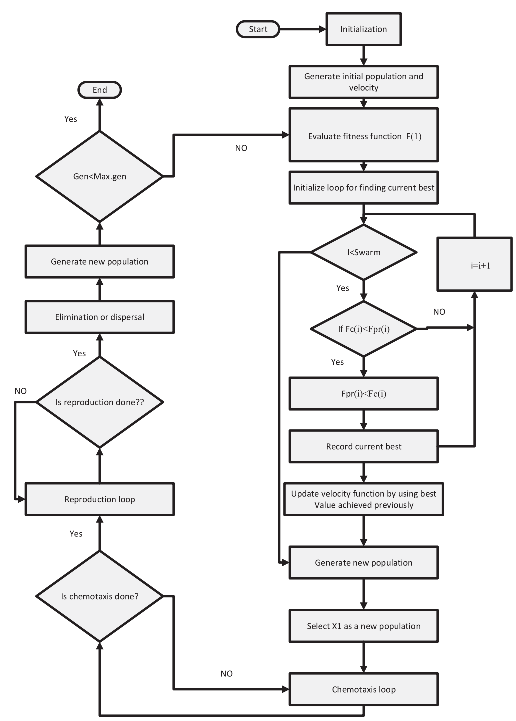


FIGURE 9. The implementation procedure of the proposed HBFPSO algorithm for DSM of residential sector, commercial sector, and industrial sector.

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
      $\theta(i, :) = \theta(i, :) + C_i \frac{\Delta_i}{\sqrt{\Delta_i^T \Delta_i}}$
      for $d = 1{:}\ (m - 1)$ **do**
        Compute fitness: $J = Fit\_function(i)$
      end
      $s = 0$ **while** $s < N_s$ **do**
        swimming loop
      end
      if $J(i) = J\_last(i)$ **then**
        evaluating fitness
      end
      $J(i) = J(i)$ Determine new position $\theta(i, :)$
      for $d = 1{:}\ (m - 1)$ **do**
        Determine fitness function $Fit\_function(i)$
      end
      else
      end
      $s = N_s$
      Current best state of appliances are recorded
    end
  end
end

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

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]	$f(x) = 0.5 + \frac{Sin^2\left(\sqrt{x_1^2+x_2^2}\right)-0.5}{\left(1+0.001(x_1^2+x_2^2)\right)^2}$
Non-continuous Rastrigin	[−5.12, 5.12]	[−5.12, 2]	$\sum_{i=1}^{D}\left(y_i^2 - 10cos(2\pi y_i) + 10\right)$ $y_i = \begin{cases} x_i & \lvert x_i\rvert < \frac{1}{2} \\ \frac{round(2x_i)}{2} & \lvert x_i\rvert \geq \frac{1}{2} \end{cases}$
Weierstrass	[−0.5, 0.5]	[−0.5, 0.2]	$\sum_{i=1}^{D}\left(\sum_{k=0}^{k_{\max}}\left[a^2\cos\left(2\pi b^k\left(x_i+0.5\right)\right)\right]\right)$ $-D\sum_{k=0}^{k_{\max}}\left[a^k\cos\left(2\pi b^k 0.5\right)\right]$ $a=0.5, b=3, k_{\max}=20$

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 Function	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
HBFPSO Mean	4.76E-17	1.49E-03	1.18E-24
STD.	8.56E-16	7.35E-04	1.87E-23

EMCs in terms of cost, PAR, and CO_2 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 HBFPSO 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

Algorithm 3: The Proposed HBFPSO 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 $Vmax$, $Vmin$, $iter$, Nr, Nc, Np, $maxgen$, $maxpop$
for $horbp = 1{:}24$ **do**
  Initialize velocity by using (43);
  for $j = 1{:}swarm$ **do**
    Update velocity by using (44);
    if $vnew < Vmax \&\& vnew > Vmin$ **then**
      $vnew(i, j) = vnew(i, j)$
      else
    end
    if $vnew < Vmin$ **then**
      $vnew = Vmin$
      else
      if $vnew > Vmax$ **then**
        $vnew = Vmax$
        else
      end
    end
    popnew = X1
    BFOA steps follows after new population;
    X1 = (rand(Np, D))
    for $j = 1{:}Np$ **do**
      for $i = 1{:}D$ **do**
        if $X1(j, i) > X(j, i)$ **then**
          $X1(j, i) = 1$
          else
          $X1(j, i) = 0$
        end
        Reproduction loop
        for $k = 1{:}Nr$ **do**
          Chemotaxis loop
          for $j = 1{:}Nc$ **do**
            Take chemotaxis step
            for $i = 1{:}Np$ **do**
              gbest
              Elimination dispersial;
              For cost
              Load = power*gbest
              begin
                Scenario 1: MLP-based forecasted day-ahead price-based DR program
                Calculate cost using (33);
                For PAR
                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
              end
              begin
                Scenario 2: MLP-based forecasted CPP price-based DR program
                Calculate cost using (33);
                For PAR
                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
              end
              begin
                Scenario 3: MLP-based forecasted ToU price-based DR program
                Calculate cost using (33);
                For PAR
                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
              end
            end
          end
        end
      end
    end
  end
end

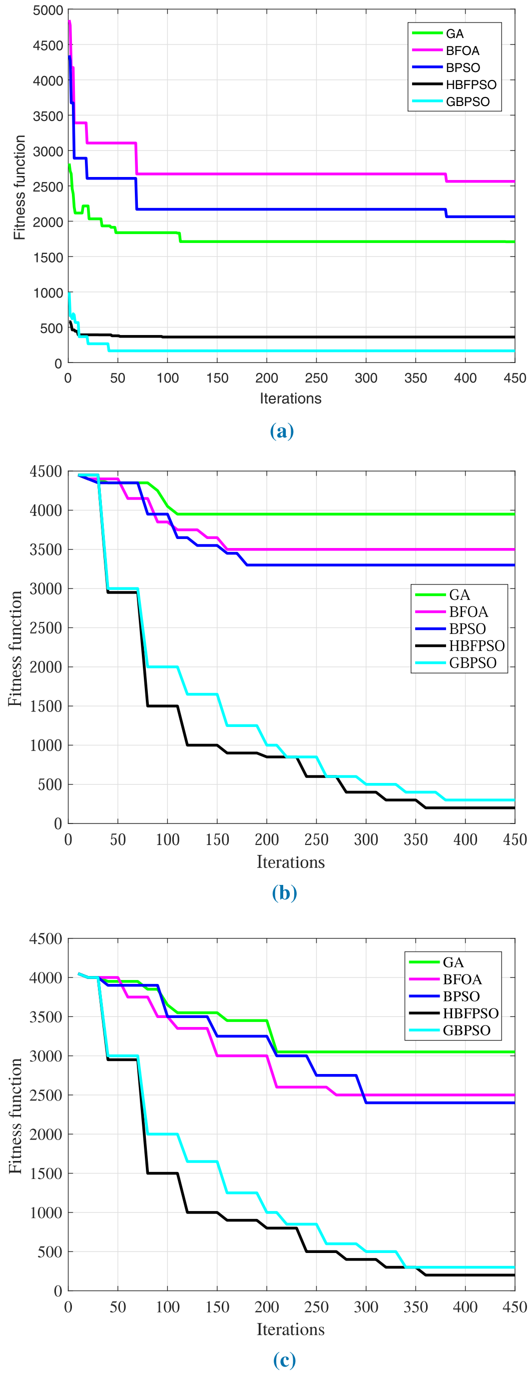


FIGURE 10. Performance evaluation of the proposed and existing algorithms using benchmark test functions: (a) Schaffer, (b) Weierstrass, (c) Non-continuous Rastrigin's.

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 HBFPSO 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

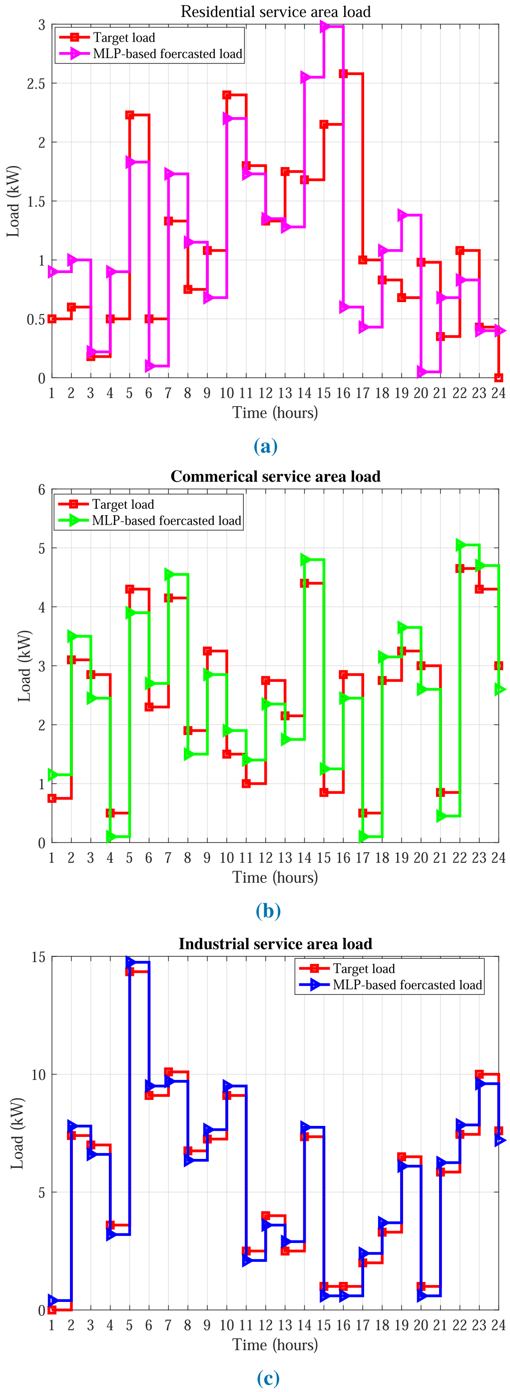


FIGURE 11. Day ahead demand side forecasted load with hour resolution for three service areas using MLP-based forecast engine: (a) Residential service area, (b) Commercial service area, (c) Industrial service area.

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,

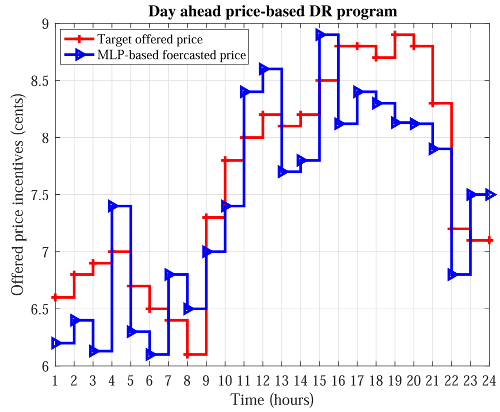


FIGURE 12. Day ahead forecasted offered price of DR with hour resolution using MLP-based forecast engine.

TABLE 10. Comparison of PAR for residential sector under DA price-based DR program.

Scheduling techniques	PAR	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	Difference	Percentage decrements
Unscheduled	4.0455		
GA	2.9245	1.121	32.16%
BFOA	3.6804	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%

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

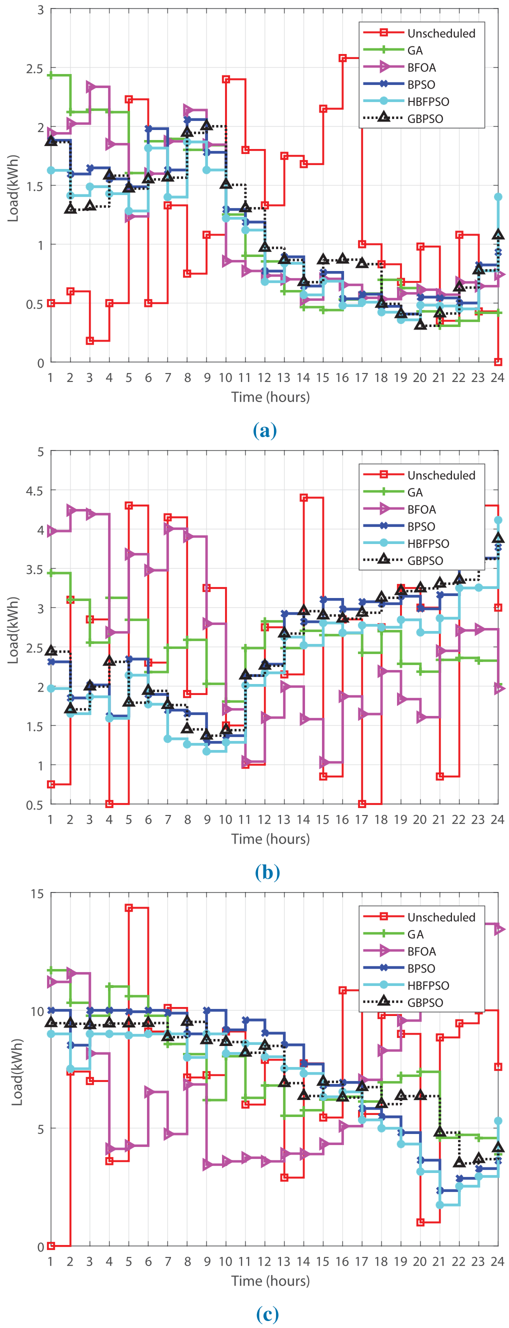


FIGURE 13. Comparison daily demand-side energy consumption profiles of the proposed and existing algorithm under DA price-based DR program: (a) Residential, (b) Commercial, (c) Industrial.

cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is \$3.9, \$3.7, \$3.8, \$3.6, \$3.3, and \$1.54, respectively. Whereas, for commercial sector the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is \$4.588, \$4.500, \$4.586, \$4.320, \$4.096, and \$4.299, respectively. Similarly, for the industrial sector, the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is \$13.42, \$13.34, \$13.32, \$12.58, \$12.14, and \$12.52, respectively. The percentage decrease in the cost of electricity achieved by different algorithms for residential, commercial, and industrial sectors is given in Tables 13, 14, and 15, respectively. Thus, both graphical and numerical results illustrate that our proposed algorithm HBFPSO-based EMC outperforms existing algorithms-based EMC in terms of electricity for all three service areas like residential, commercial, and industrial, respectively.

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	69.95%

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%

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

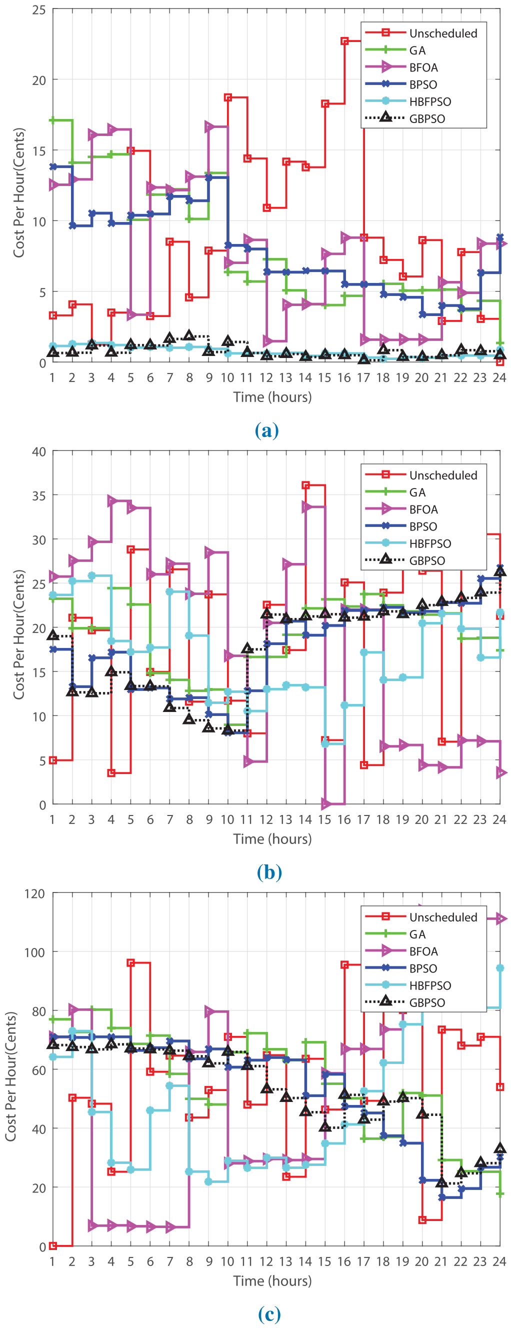


FIGURE 14. Hourly cost evaluation for the consumed electricity: (a) Residential, (b) Commercial, (c) Industrial.

GBPSO, which fair slightly better. HBFPSO 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 interruptible, portable un-interruptible, and consistent load appliances in the residential sector.

Whereas, Table 17 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%
HBFPSO	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
HBFPSO	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 Un-interruptible load	Consistent load
GA	2.7770	0.3523
BFOA	0.7675	0.2349
BPSO	1.7626	0.1041
HBFPSO	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
HBFPSO	1.7083	4.1597
GBPSO	0.7287	0.3263

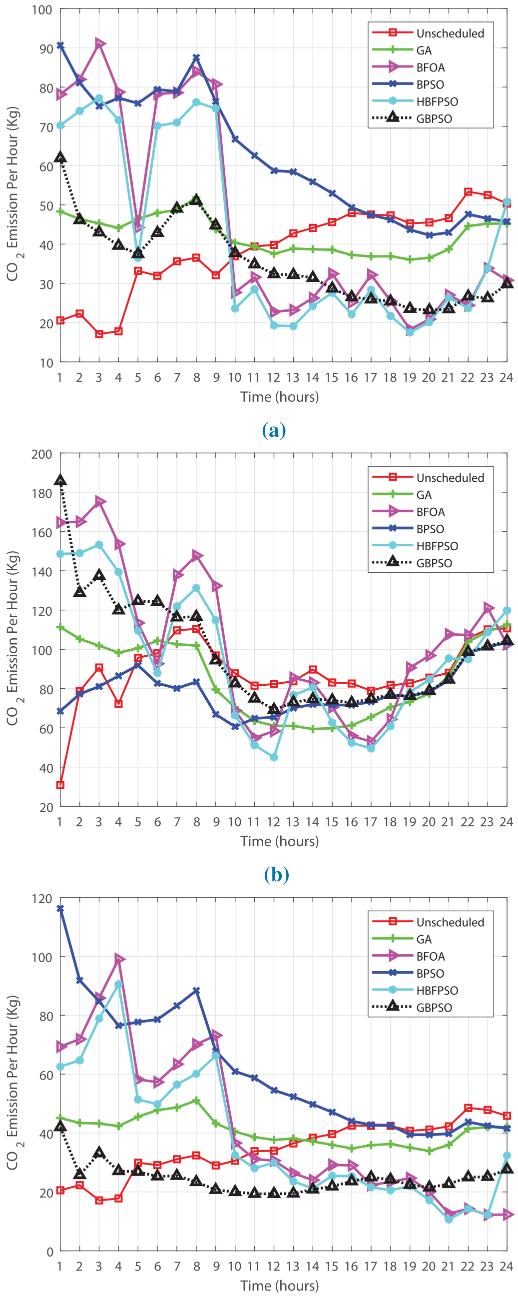


FIGURE 15. Comparison of CO_2 emissions of the proposed and existing algorithms under DA price-based DR program: (a) Residential ; (b) Commercial; (c) Industrial.

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:

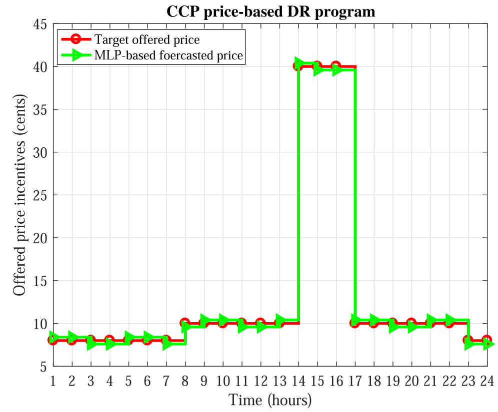


FIGURE 16. Forecasted offered critical peak price of DR using MLP-based forecast engine.

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 $3.5kWh$, $3.7kWh$, $2.6kWh$, $2.4kWh$, and $2.5kWh$, respectively. Whereas, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO for the commercial sector is limited to $4kWh$, $3.3kWh$, $1.9kWh$, $1.65kWh$, and $2.3kWh$, respectively. Similarly, for the industrial sector, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO is limited to $11kWh$, $12.2kWh$, $10kWh$, $5.89kWh$, and $5.95kWh$, 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.

TABLE 19. Comparison of PAR for residential sector under CPP DR program.

Scheduling techniques	PAR	Difference	Percentage decrements
Unscheduled	4.57		
GA	3.72	0.85	20.50%
BFOA	4.32	0.25	5.62%
BPSO	2.76	1.81	49.38%
HBFPSO	2.44	2.13	60.77%
GBPSO	2.68	1.89	52.13%

2) COST PROFILES

Figure 18 shows the cost profiles for different algorithms across different sectors. For the residential sector, the daily

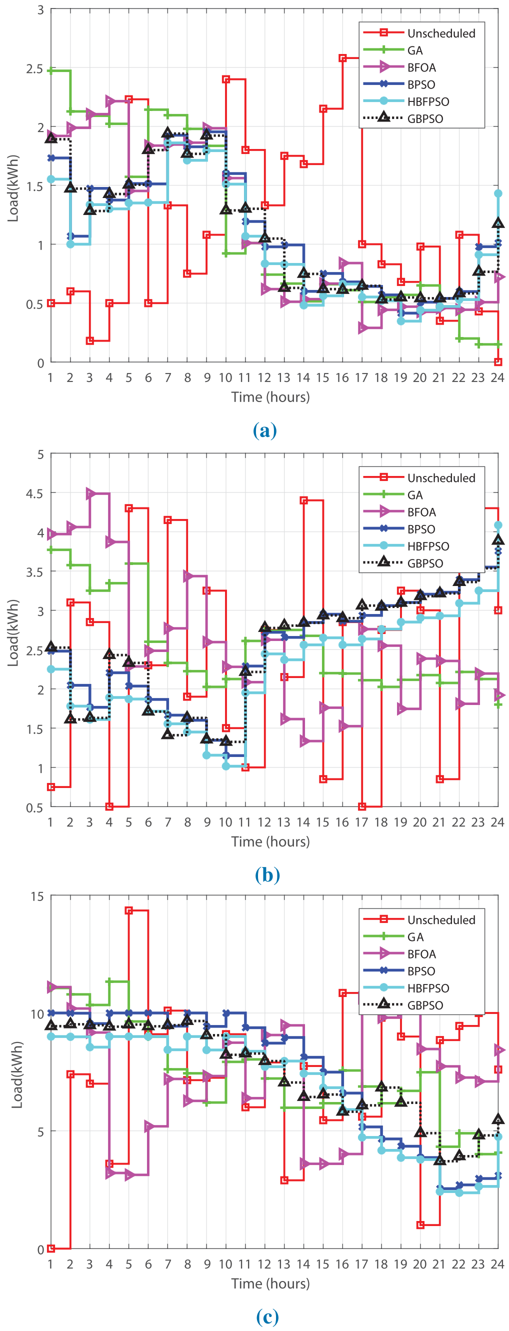


FIGURE 17. Comparison daily demand-side energy consumption profiles of the proposed and existing algorithm under CPP price-based DR program: (a) Residential ; (b) Commercial; (c) Industrial.

cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is \$7.5, \$5.56, \$6.56, \$4.08, \$2.8, and \$4, respectively. Whereas, for commercial sector the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is \$8, \$7.39, \$7.74, \$4.856, \$2.88, and \$4.852, respectively. Similarly, for the industrial sector, the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, and GBPSO is \$23.55, \$19.89, \$20.99, \$14.17, \$8.1, and \$14.11, respectively.

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%
HBFPSO	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%
HBFPSO	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%
HBFPSO	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%
HBFPSO	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

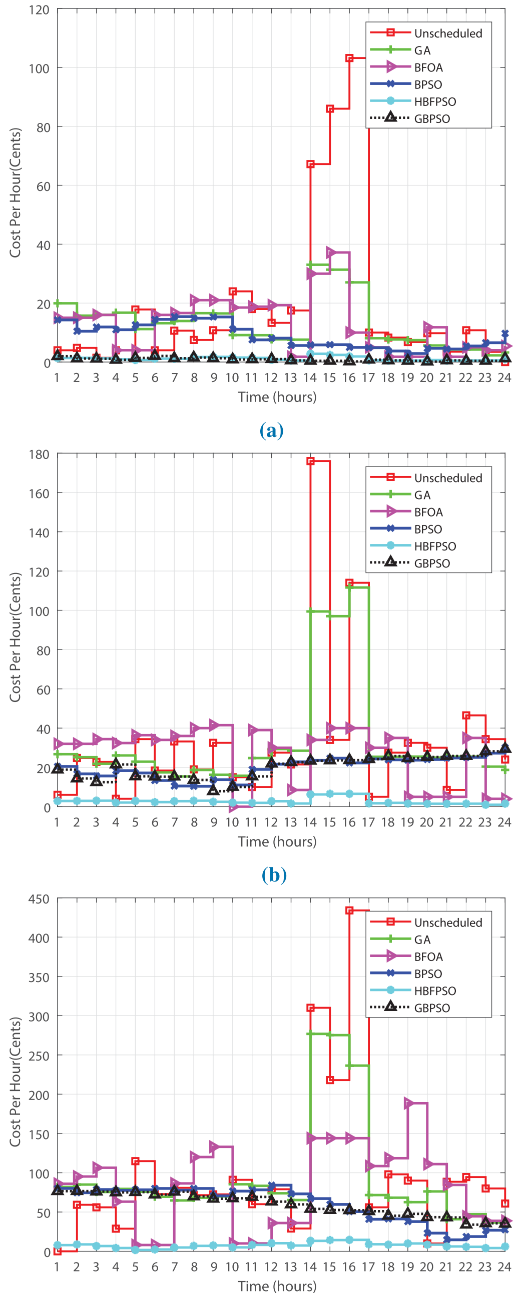


FIGURE 18. Comparison of hourly cost of the proposed and existing algorithms under CPP DR program: (a) Residential, (b) Commercial, (c) Industrial.

proposed HBFPSO algorithm results in the least amount of CO_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.

TABLE 24. Comparison of cost of the proposed and existing algorithms under CPP DR program for industrial sector.

Scheduling techniques	Cost	Difference	Percentage decrements
Unscheduled	2355.2		
GA	2099.7	255.5	11.47%
BFOA	1989.5	365.7	16.83%
BPSO	1417.6	937.6	43.62%
HBFPSO	1281.5	1073.7	45.58%
GBPSO	1411.8	943.4	40.05%

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

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

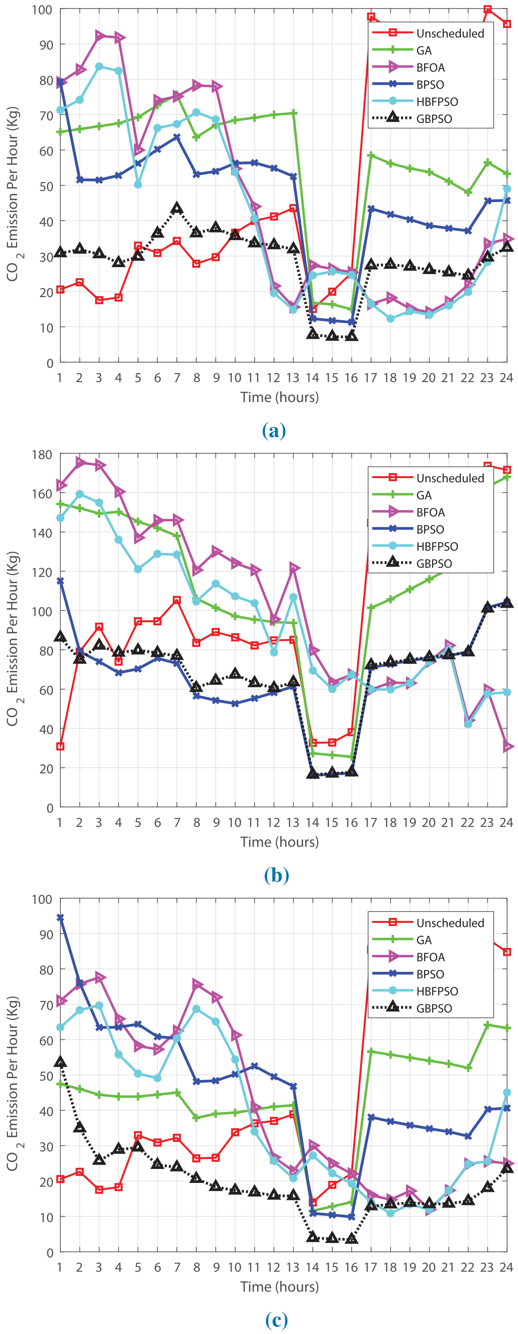


FIGURE 19. Comparison of CO_2 emissions of the proposed and existing algorithms under CPP DR program: (a) Residential, (b) Commercial, (c) Industrial.

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:

TABLE 27. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under CPP DR program for industrial sector.

Scheduling techniques	Portable interruptible load	Consistent load
GA	1.4	0.6
BFOA	0.5	1.75
BPSO	0.8	0.45
HBFPSO	1.8	4.2
GBPSO	0.7	0.4

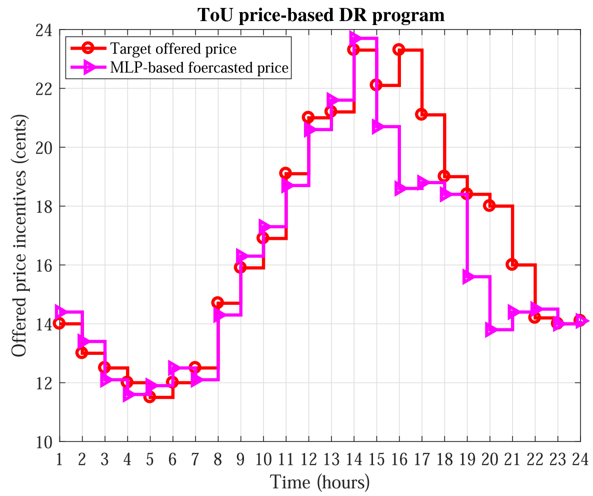


FIGURE 20. Forecasted ToU price-based DR program using MLP-based forecast engine.

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 3.4kWh, 3.6kWh, 2.6kWh, 2.6kWh, and 2.4kWh, respectively. Whereas, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO for the commercial sector is limited to 4kWh, 3.9kWh, 2.3kWh, 2kWh, and 2.5kWh, respectively. Similarly, for the industrial sector, the scheduled energy consumption of GA, BFOA, BPSO, HBFPSO, and GBPSO is limited to 11kWh, 12kWh, 9kWh, 5.8kWh, and 5.88kWh, 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

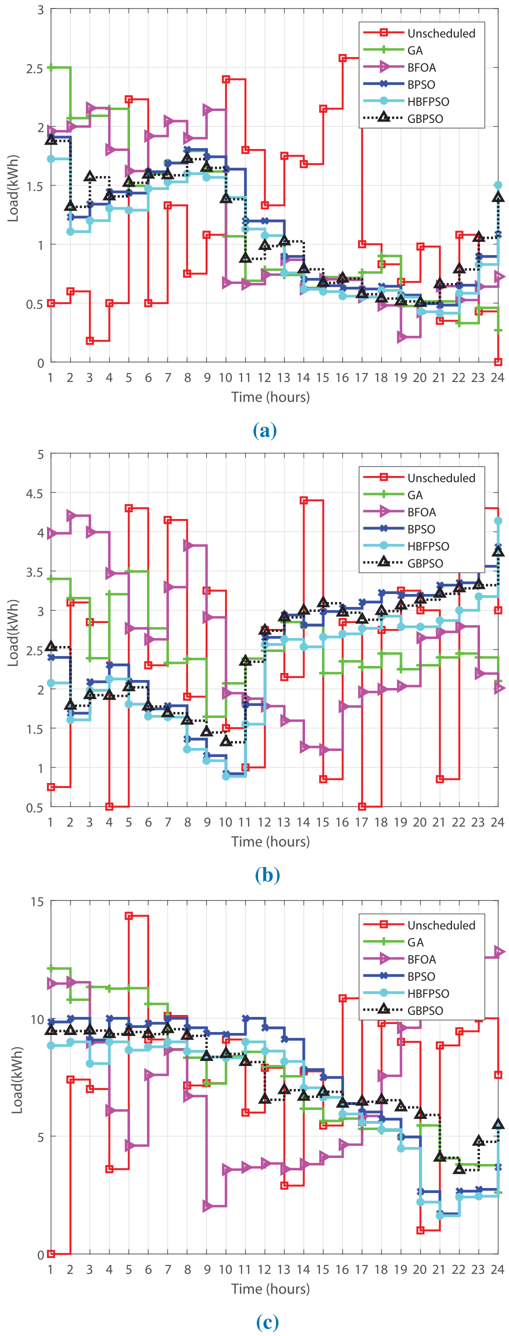


FIGURE 21. Comparison of demand-side energy consumption profiles of the proposed and existing algorithms under ToU price-based DR program: (a) Residential, (b) Commercial, (c) Industrial.

commercial sector the daily cost of electricity without load scheduling and load scheduling using BFOA, GA, BPSO, HBFPSO, 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, HBFPSO, 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.

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%
HBFPSO	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%
HBFPSO	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%
HBFPSO	1.65	2.12	78.22%
GBPSO	1.77	2	72.20%

TABLE 31. Comparison of cost of the proposed and existing algorithms under ToU price-based DR program for residential sector.

Scheduling techniques	Cost	Difference	Percentage decrements
Unscheduled	878.69		
GA	827.08	51.61	6.05%
BFOA	773.35	105.34	12.75%
BPSO	718.39	160.3	20.07%
HBFPSO	650.76	228.76	26.03%
GBPSO	671.98	206.71	23.52%

3) CO_2 EMISSIONS

Figure 23 shows the hourly CO_2 emissions for residential, commercial, and industrial sectors. It can be observed that all the algorithms show similar results in reducing CO_2 emissions. Our proposed HBFPSO shows better result in term of

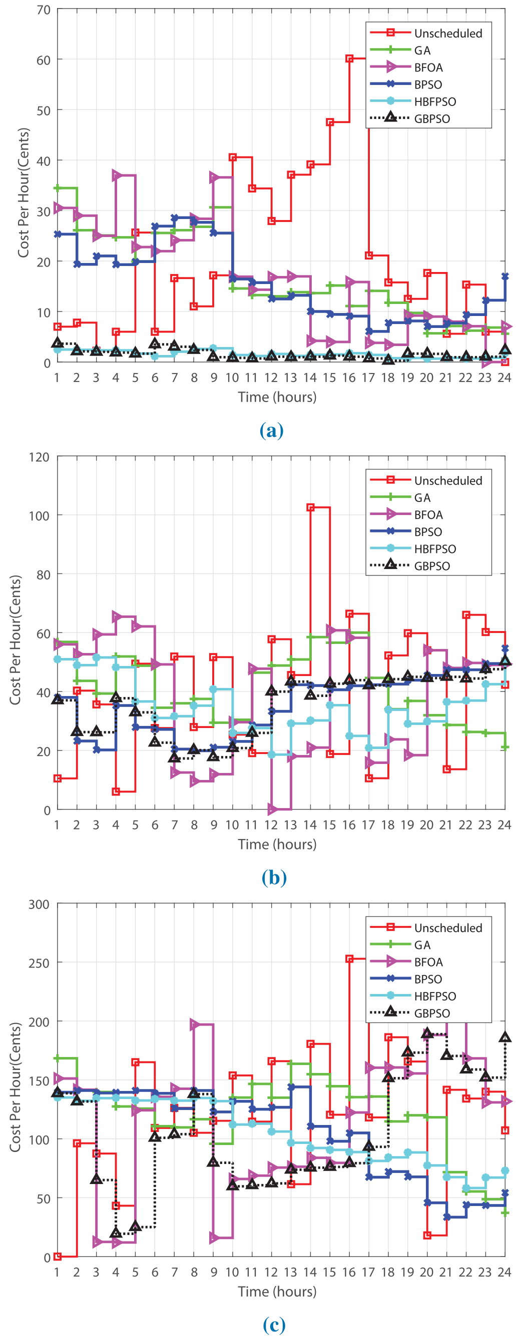


FIGURE 22. Comparison of hourly cost of the proposed and existing algorithms under ToU price-based DR program: (a) Residential, (b) Commercia, and (c) Industrial.

reduction of CO_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.

TABLE 32. Comparison of cost of the proposed and existing algorithms under ToU price-based DR program for commercial sector.

Scheduling techniques	Cost	Difference	Percentage decrements
Unscheduled	962.55		
GA	957.82	4.73	0.5%
BFOA	904.05	58.5	6.26%
BPSO	855.15	107.41	11.81%
HBFPSO	825.62	136.93	15.31%
GBPSO	855.16	107.52	11.85%

TABLE 33. Comparison of cost of the proposed and existing algorithms under ToU price-based DR program for industrial sector.

Scheduling techniques	Cost	Difference	Percentage decrements
Unscheduled	2817		
GA	2720	97	3.50%
BFOA	2679	138	5.02%
BPSO	2490	327	12.32%
HBFPSO	2446	371	14.09%
GBPSO	2498	328	12.34%

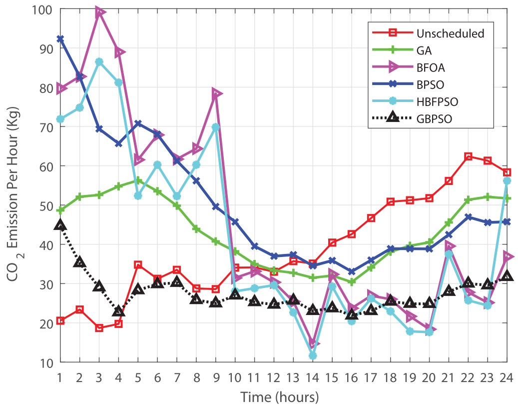
TABLE 34. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under ToU price-based DR program.

Scheduling technique	Portable interruptible load	Portable Un-interruptible load	Consistent load
GA	2.11	5.15	0.51
BFOA	0.7	1.1	0.45
BPSO	1.28	1.68	0.4
HBFPSO	1.92	1.42	4.54
GBPSO	1.25	1.59	0.38

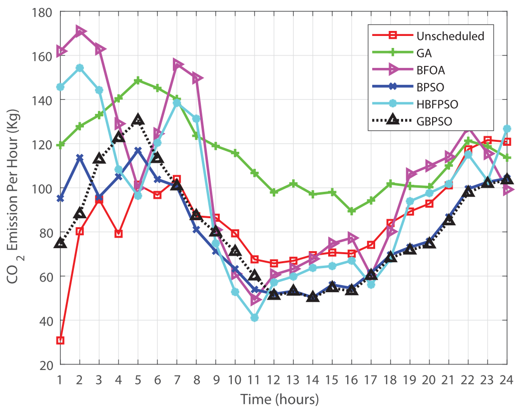
Whereas, Table 35 shows the time delay for each load category, i.e., portable un-interruptible and consistent load appliances in commercial sector. Similarly, Table 36 shows the time delay for each load category, i.e., portable interruptible and consistent load appliances in the industrial sector.

TABLE 35. Comparison of user comfort in terms of delay time of the proposed and existing algorithms under ToU price-based DR program for commercial sector.

Scheduling techniques	Portable Un-interruptible load	Consistent load
GA	2.33	0.23
BFOA	1.29	0.19
BPSO	0.87	0.05
HBFPSO	2.05	5.26
GBPSO	1.35	0.08



(a)



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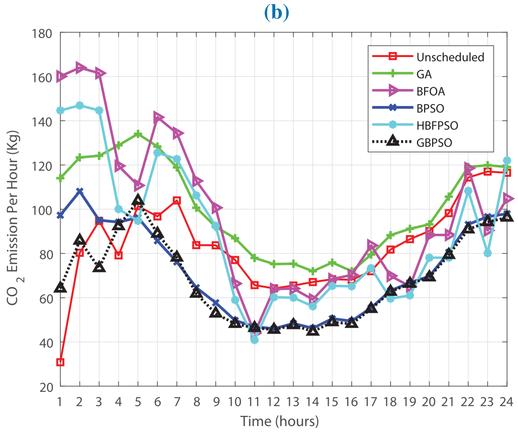

(c)

FIGURE 23. **Comparison of CO_2 emissions of the proposed and existing algorithms under ToU price-based DR program: (a) Residential, (b) Commercial, (c) Industrial.**

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 CO_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_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. 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

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.**

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

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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