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An Innovative Optimization Strategy for Efficient Energy Management With Day-Ahead Demand Response Signal and Energy Consumption Forecasting in Smart Grid Using Artificial Neural Network

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ABSTRACT In this study, a novel framework is proposed for efficient energy management of residential buildings to reduce the electricity bill, alleviate peak-to-average ratio (PAR), and acquire the desired trade-off between the electricity bill and user-discomfort in the smart grid. The proposed framework is an integrated framework of artificial neural network (ANN) based forecast engine and our proposed day-ahead grey wolf modified enhanced differential evolution algorithm (DA-GmEDE) based home energy management controller (HEMC). The forecast engine forecasts price-based demand response (DR) signal and energy consumption patterns and HEMC schedules smart home appliances under the forecasted pricing signal and energy consumption pattern for efficient energy management. The proposed DA-GmEDE based strategy is compared with two benchmark strategies: day-ahead genetic algorithm (DA-GA) based strategy, and day-ahead game-theory (DA-game-theoretic) based strategy for performance validation. Moreover, extensive simulations are conducted to test the effectiveness and productiveness of the proposed DA-GmEDE based strategy for efficient energy management. The results and discussion illustrate that the proposed DA-GmEDE strategy outperforms the benchmark strategies by 33.3% in terms of efficient energy management.

INDEX TERMS Advanced metering infrastructure, artificial neural networks, demand response, energy management, grey wolf modified enhanced differential evolution algorithm, smart grid.

NOMENCLATURE

SG	Smart grid
ANN	Artificial neural network
HEMS	Home energy management system
MILP	Mixed integer linear programming
BBSA	Binary backtracking search algorithm
IGA	Internal genetic algorithm
OPSO	Outer particle swarm optimization
ILP	Integer linear programming
DR	Demand response
RTPS	Real-time pricing scheme
DSM	Demand side management
AMI	Advanced metering infrastructure
TLBOA	Teaching and learning based optimization algorithm
SFL	Shuffled frog leaping algorithm

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ToUPS	Time of use pricing scheme
IBRS	Inclined block rate pricing scheme
SSA	Salp swarm algorithm
RFA	Rainfall algorithm
BPOA	BAT pollination optimization algorithm
DRTA	Distributed real-time algorithm
DDT	Dual decomposition technique
ACLPS	Adaptive consumption level pricing scheme
VPPS	Variable peak pricing scheme
DAPS	Day-ahead pricing scheme
FPS	Flat pricing scheme
SSM	Supply side management
RTAs	Real-time appliances
MOAs	Manually operated appliances
AOAs	Automatically operated appliances
SAs	Schedulable appliances
IA	Interruptible appliances
NIA	Non-interruptible appliances
SL	Schedulable load
NSL	Non-schedulable load
TFA	Time flexible appliances
PFA	Power flexible appliances
EA	Essential appliances
HEMC	Home energy management controller
ICT	Information and communication technologies
MINLP	Mixed integer non-linear programming
PAR	Peak-to-average ratio
GWO	Grey wolf optimization
DE	Differential evolution algorithm
EDE	Enhanced differential evolution algorithm
mEDE	Modified enhanced differential evolution algorithm
HAN	Home area network
EM	Energy management
W/O	Without scheduling
DA-GA	Day-ahead genetic algorithm
DA-GmEDE	Day-ahead grey wolf modified enhanced differential evolution algorithm
PSA	Power shiftable appliances
TSA	Time shiftable appliances
CA	Critical appliances
GmEDE	Grey wolf modified enhanced differential evolution algorithm
BFOA	Bacteria foraging algorithm
MPSOA	Modified particle swarm optimization algorithm
GA	Genetic algorithm
χ_i^{t+1}	Status in the next timeslot
r_i^t	Number of remaining timeslots
w_i^t	Number of waiting timeslots
X_i^t	Appliance ON/OFF indicator
E_i^A	Aggregated energy consumption
C_i^A	Aggregated cost
κ	Scheduling set
F_i^t	Time flexibility
ω_i^t	A parameter that varies w.r.t. timeslot
$\hat{E}_i^t$	Normal energy consumption
Δ	Small change
ς	Countermeasure at both extremes of deviation
d_i^A	Total discomfort for shiftable of appliances
$d_p^{A_2^P}$	Discomfort caused to power shiftable appliances
R_A^P	PAR
$\gamma_1, \gamma_2, \gamma_3$	Weights for trade-off adjustment
p_i^r	Power rating of the appliances
i	An appliance
t	Timeslot
K	Real number garter than 1
ρ_t^f	Forecasted pricing signal
$v_{n+1}(i)$	Updated velocity
fit	Fitness
H	Overall scheduling time horizon
A_1^T	Time shiftable appliances
A_2^P	Power shiftable appliances
A_3^C	Critical appliances
α_i	Operation starting time
β_i	Operation end time
E_i^t	Energy consumption
$p_i^{r\ \min}$	Minimum rated power
$p_i^{r\ \max}$	Maximum rated power
$Mitr$	Maximum iteration
R	Crossover rate
χ_i^t	Current status of an appliance
T_i^{lo}	Length of operation time

I. INTRODUCTION

The energy demand has dramatically increased with continuous population and economic growth. At the same time, the pressure on the utility companies and environment has also increased rapidly. There are two methods available in practice to cope with this increasing energy demand: (i) generation side management (GSM), and (ii) demand side management (DSM). The first approach is related to increasing the capacity of generation units. Whereas, the second approach involves management of users' energy consumption either by load management or demand response (DR) programs. The DR programs are of two types: (i) incentive-based DR program, and (ii) price-based DR program [1]. The first type uses direct load control in which the utility company directly controls the load of the consumers on a short notice when required. The second type uses price-based DR program [2], where the utility company encourages users to manage their energy consumption via scheduling by home energy management controller (HEMC) in response to day-ahead pricing signal.

The focus of this study is on efficient energy management by scheduling energy consumption of homes using price-based DR program. With this motivation, the residents can reduce their electricity bill via scheduling load of their homes with day-ahead pricing signal. To this end, some analytical and heuristic schemes are developed for power scheduling of smart homes. In [3] and [4], authors used mixed integer linear programming (MILP) to schedule the energy consumption of their homes under dynamic pricing scheme to minimize the electricity bill and smoothen the demand curve. However, these objectives are achieved at the cost of increased system complexity. The authors used mixed integer non-linear programming (MINLP) in [5] and [6] to schedule multi-class appliances of residential buildings under real-time pricing scheme (RTPS) to reduce the electricity bill. However, peaks in demand may emerge during the timeslots where electricity price is low. In [7], [8], and [9], authors used heuristic algorithms like bacteria foraging algorithm (BFOA), modified particle swarm optimization algorithm (MPSOA), and genetic algorithm (GA), respectively, to schedule the residential load for cost-efficient solutions. However, cost-efficient solutions are obtained at the expense of consumers' discomfort and increased peak-to-average ratio (PAR). A game theoretic home energy management system (HEMS) is proposed for energy consumption scheduling of residential buildings under DR pricing schemes to reduce PAR and electricity bill in [10], [11]. However, these studies do not consider the trade-offs between the electricity bill and user-discomfort. Moreover, the appliances priority and day-ahead price forecasting are not considered, which are useful in the efficient energy management of smart homes.

Hence, this work is focused on developing an innovative optimization strategy for efficient energy management of residential buildings with day-ahead DR pricing signal and energy consumption forecasting using artificial neural network (ANN). The purpose is to reduce electricity bill, PAR, and acquire minimum acceptable trade-off between electricity cost and discomfort. The main contributions and distinguishing features of this paper are as follows:

- A forecast engine based on ANN is coupled with energy management model to forecast the day-ahead DR pricing signal and energy consumption. The purpose is to perform efficient energy management via scheduling energy usage profile of residential buildings under the forecasted DR pricing signal.
- We propose grey wolf modified enhanced differential evolution (GmEDE) algorithm, which is a hybrid of grey wolf and modified version of enhanced differential evolution algorithm. The proposed optimization algorithm takes into account constraints, occupant energy consumption pattern, and DR pricing signal to perform efficient energy management.
- In addition to electricity cost and PAR objectives, which are handled in [7]–[9], we formulate and investigate consumers' comfort and discomfort while solving the energy management problem with day-ahead (DA) forecasted DR pricing signal and energy consumption using ANN based forecaster.
- The proposed DA-GmEDE based strategy is compared with two benchmark strategies: day-ahead genetic algorithm (DA-GA) based strategy and day-ahead game-theory (DA-game-theoretic) based strategy, in terms of performance parameters like electricity cost, PAR, and the trade-off between electricity bill and user-discomfort.

The remainder of the paper is organized as follows: The related work is discussed in Section II. The proposed framework and its mathematical modeling is demonstrated in Section III. Problem formulation and proposed strategy are discussed in Section IV and Section V, respectively. In Section VI, simulation results and discussion are presented. Finally, the paper is concluded in Section VII along with a discussion on possible future directions. The acronyms and notations used in this paper are defined in **NOMENCLATURE**.

II. RELATED WORK

With the emergence of information and communication technologies (ICTs) and advanced metering infrastructure (AMI), residents can take part in DSM either by price-based DR programs or by incentive-based DR programs to cope with the effects of increasing energy demand. With this incentive, several schemes for energy management by way of scheduling energy consumption of residential buildings have been proposed. In [12], authors schedule household appliances using binary backtracking search algorithm (BBSA) to reduce energy consumption and electricity cost. However, peaks in demand may emerge when most appliances are shifted to low price hours. In [13], authors schedule the power usage pattern of residential buildings without affecting the operation of non-shiftable appliances. The purpose is to reduce the electricity cost. However, cost reduction is not possible without introducing delay to home appliances. Authors proposed an energy management model for monitoring both intrusive and non-intrusive load in [14] to reduce electricity cost and greenhouse gas emissions. However, the electricity expenses are reduced at the cost of user-comfort. An optimization model is proposed for household load scheduling under combined real-time pricing scheme (RTPS) and inclined block rate scheme (IBRS) to reduce the electricity cost [15]. In [16], a HEMS for optimal scheduling of controllable appliances under distributed generation integrated with energy storage system is proposed. However, demand is fully satisfied by providing continuous supply at the expense of high capital cost. The electricity bill and peaks in demand are reduced simultaneously by scheduling household load in [17]. However, the assumptions made in the strategy seem impractical. Various schemes for power usage pattern scheduling via home area network (HAN) are proposed in [19]–[22]. In [23], authors schedule the power consumption of homes under price-based DR program using teaching-learning based optimization algorithm (TLBOA) and shuffle frog leaf algorithm (SFLA), in order to reduce total bill for the consumed energy. However, the user-comfort and PAR are ignored, which are directly linked with total electricity bill. Authors in [24]–[31] proposed heuristic algorithms based optimization models for household load scheduling to reduce overall electricity bill and PAR. However, these objectives are obtained at the expense of consumers' frustration.

In [32] and [33], authors performed energy consumption scheduling using DR program to match the ever increasing demand with available power supply. The objectives are to maximize social welfare and reduce energy bills by effectively managing the demand with power supply. The price-based DR programs include critical peak pricing scheme (CPPS), time of use pricing scheme (ToUPS), RTPS, and day-ahead pricing scheme (DAPS). The electricity cost is usually determined by using ToUPS, DAPS, and CPPS. However, CPPS adds peak price to ToUPS and there is a chance of peak emergence in low price hours, which can overload the power systems [34]. In contrast, DAPS has more flexibility and changes as often as hourly, which better reflects the varying energy consumption of residential buildings. Thus, several models have proposed to solve energy management problem of residential buildings using MILP based models [35], fuzzy logic based models [36], and game-theory based models [37]. A household energy consumption model for day-ahead planning of residential microgrid is developed in [38]. The homes are equipped with electric vehicles (EVs), photovoltaic systems, and energy storage systems (ESSs) to participate in DR programs. The residential microgrid is grid-connected microgrid and participates in Bi-directional power flow and communications. However, the objectives are achieved at the cost of increased complexity and computation overhead.

A mechanism for power scheduling of domestic load in a home area network is proposed in [35]. The purpose of this study is to create balanced load schedule based MILP in order to reduce energy cost and power peaks. However, the peaks in demand may emerge in high-price hours, which is a threat to the utility grid station. In [39], authors developed an efficient energy management framework with day-ahead energy forecasting in smart microgrids. Efficient energy management is conducted by scheduling household load, and charging/discharging of EVs by mixed integer linear programming (MILP). The aim is to lessen the bill, user-discomfort, and PAR. However, the objectives are obtained at the expense of increased execution cost. A stochastic model is proposed to perform energy management of a home having load, photovoltaic array, plug-in electric vehicle (PEV), and heat pump [40]. First, photovoltaic array, PEV, and heat pump energy profile are forecasted based on stochastic methods. Then, the forecasted results are utilized for efficient energy management of a smart home. The model efficacy is tested by comparing it with benchmark models. However, the schemes for efficient energy management are not mentioned. Authors in [41] proposed an integrated framework of machine learning, optimization, and DR program for efficient energy management of smart homes. The purpose is to investigate the performance of learning-based energy management system in the DR framework. However, the machine learning models are not utilized to forecast the energy consumption pattern.

In [42], a robust ensemble learning-based framework is developed to forecast household power usage profile for energy management. The proposed model has improved performance as compared to the existing models in terms of accuracy. However, only forecasting is performed through ensemble model and energy management aspects are not considered. An energy management system with day-ahead solar irradiation forecasting using ANNs is proposed in [43]. The aim is to accurately forecast global solar irradiance using meteorological data with the help of ANNs. However, the energy management aspects are ignored.

The recent and relevant literature available on the above theme is summarized in Table 1. Although, all the schemes discussed above are efficient in energy management by scheduling household appliances, however, because of the non-linear behavior of both consumers and pricing signals, these schemes fail to handle the energy consumption pattern scheduling of residential buildings in real-time. Moreover, there is no universal model/strategy to perform optimal energy management via power usage scheduling residential buildings in real-time; some models are better for some specific objectives and conditions. In this regard, an innovative optimization framework composed of ANN based forecaster and GmEDE algorithm based HEMC is proposed in this research for efficient energy management of the residential buildings.

III. PROPOSED FRAMEWORK FOR EFFICIENT ENERGY MANAGEMENT OF RESIDENTIAL BUILDINGS

The objective of the proposed framework is to minimize the electricity bill, reduce PAR, and acquire the desired trade-off between the electricity cost and user-discomfort by scheduling the electricity consumption of residential buildings with day-ahead price forecast using ANN, subject to power system stability. The proposed framework comprises utility companies, ANN based forecasters, and residential buildings embedded with GmEDE based HEMC. The focus of this work is on efficient energy management of the residential buildings. A home in residential buildings is mainly comprised of HEMC, AMI, home appliances, in-home display (IHD), and smart meters. The entire framework for efficient energy management of residential buildings is depicted in Figure 1. First, ANN-based forecaster is implemented that receives historical price-based DR and energy consumption data for the utility company and forecasts day-ahead pricing signal and energy consumption pattern. Then, HEMC (see Section IV) based on DA-GmEDE strategy (see Section V) is implemented, which receives day-ahead pricing signal and energy consumption pattern to perform efficient energy management. The detailed description is as follows:

The ANN-based forecaster in our work is chosen due to its potential for handling non-linear relationships between the

TABLE 1. A brief review of relevant literature interms of techniques, DR programs, Appliances category, objectives, and limitations.

Energy management models	Techniques	DR programs	Appliances categorization	Objectives	Limitations
Residential HEMS [12]-[20]	BBSA, MILP, Dijkstra, IGA, OPSO, ILP	RTPS+IBRS, ToUPS, and RTPS	RTAs, MOAs, and AOAs, and SAs	Electricity payment and energy consumption reduction	User-comfort is compromised in order to reduce energy cost and consumption
Optimal household appliance scheduling [16]	TLBO and SFL algorithms	ToUS, RTPS, and CPPS	NSL and SL	Total payments reduction	The total electricity cost is reduced at the expense of user comfort
Comfort aware HEMS [21]	ILP	DAPS and FPS	TFA and PFA	Desired trade-off between bill payment and discomfort achievement	The PAR is ignored, which has influenced discomfort and electricity cost
HEMS via HAN [22]	WSN, ZigBee, Wi-Fi, and Z-Wave	RTPS	IA and NIA	Electricity payment and carbon emission reduction	The comfort of the user is compromised.
Heuristic based HEMS [24]- [31]	Heuristic optimization algorithms	DAPS, RTPS+IBRS, ToUPS, CPPS, and VPPS	TFA, PFA, EA	Electricity cost and PAR reduction with affordable execution time	The electricity cost and PAR is reduced at the cost of very high execution
A novel DR program [32]	ToUPS, RTPS, and CPPS	ACLPS	Overall household load	Energy bill reduction	The comfort of the user is compromised while reducing energy bill
Energy consumption scheduling of homes in SG [33]	DR program	DRTA and DDT	Aggregated household load	Potential benefits provisioning to the society	The benefits to the society are provided at the cost of high computational complexity
Fuzz controller based HEMS [36]	ToUPS, RTPS, and IBRS	BPOA	SFA and NSFA	Energy consumption, electricity bill, and PAR reduction with affordable waiting time	The complexity of the system is increased
Domestic load scheduling [35]	RTPS	MILP	SFA and NSFA	Total energy bill and power peaks reduction	The balanced load schedule is achieved at the cost of slow convergence rate
Residential load scheduling [37]	Enhanced TOUS	Game-theoretic, SSA, and RFA	NIA, IA, and NSAs	Electricity cost and power peaks reduction	The electricity bill is reduced at the cost of user discomfort

input and the output. The proposed forecaster is data driven, i.e., it is trained and enabled via learning to forecast day-ahead DR pricing signal and energy consumption pattern. The dataset used for network training is obtained from the report of midwest independent system operator (MISO) taken from federal energy regulatory commission (FERC) [44].

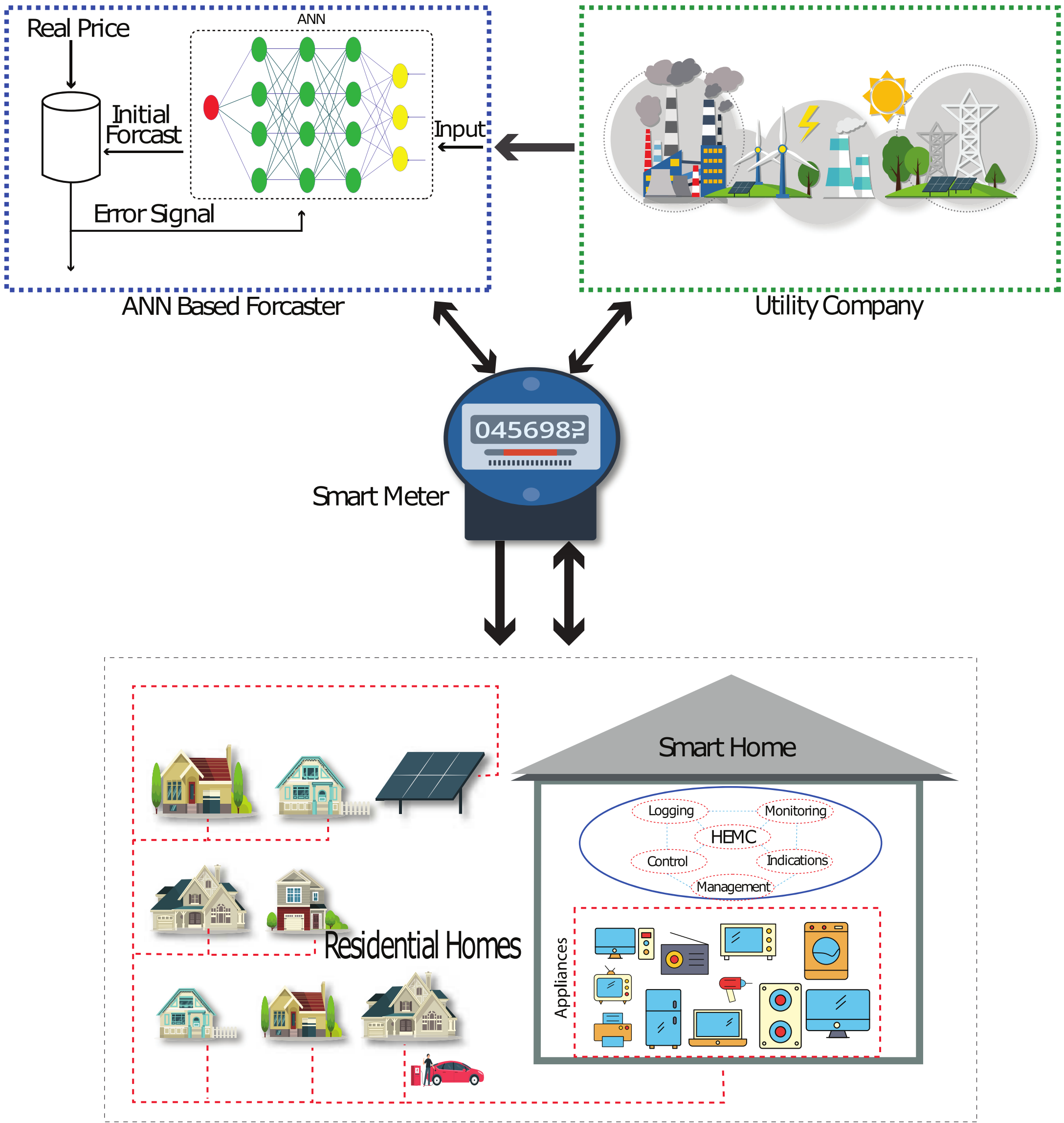

FIGURE 1. Schematic diagram and main procedure of the proposed framework for efficient energy management of residential buildings with day-ahead ANN based forecast engine. Single arrowhead denotes one-way flow and double arrowhead denotes two-way flow.

The dataset consists of hourly electricity price data and load data during the period of one year from September 2006 to September 2007. The employed data is divided into three sets: training set (9 months), testing set (1 month), and validation set (2 months). The ANN based forecaster has three layers: input layer, hidden layer, and output layer. These layers have a number of artificial neurons. The ANN is fully connected feed-forward network where neurons of each layer are connected to the neurons of succeeding layer via synaptic weights, as depicted in Figure 2.

The inputs are selected from the available historical dataset where ANN maps the input vector $Z(t)$ to the output vector $F(t)$. The output of the ANN is given as:

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

where

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

$F(t)$ is the output vector, which represents the day-ahead forecasted results, W_i is the weight factor between input and output nodes, β_j is the linear weight between input and output nodes, z_j represents input elements, and y_i is the input to the hidden nodes. The Levenberg–Marquardt optimization algorithm and sigmoidal transfer function are used for training of the ANN. The y_i is computed as follows:

$$y_i = \sum_{j=1}^{3} w_{ij} z_j + b_i, \tag{2}$$

where w_{ij} is the weight between the neurons of input layer and hidden layer, and b_i is the bias added at the hidden layer.

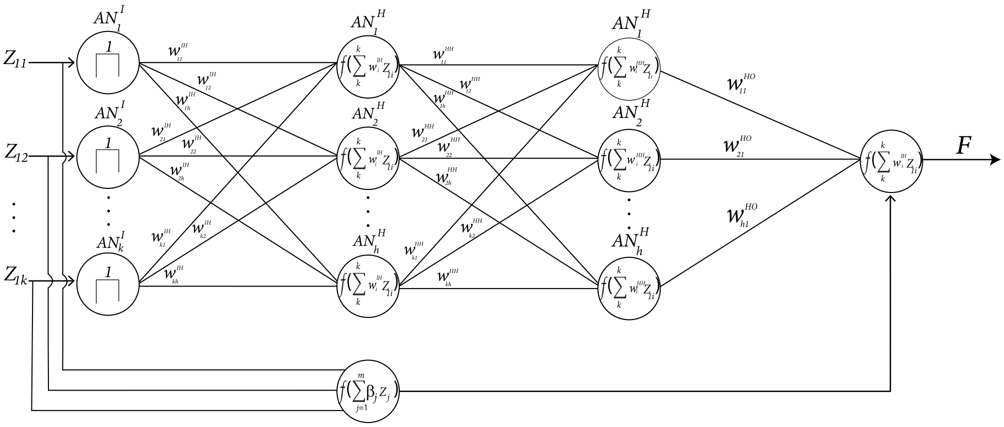

FIGURE 2. A day-ahead feed-forward ANN-based forecast engine with single input layer, two hidden layers, and an output layer forecasting DR signal and energy consumption pattern for efficient energy management.

The learning process will be stopped when the maximum number of epochs are reached or error function is minimized to the predefined tolerance. The error function is defined as follows:

$$E = \frac{1}{N}\sum_{k=1}^{N}(A_k - F_k)^2, \tag{3}$$

where A_k and F_k are the actual and forecasted outputs of the network at kth pattern, respectively, and N is the number of training samples employed. The AMI is the central nervous system and a key element of the proposed framework, which establishes advanced communication infrastructure between the utility company and smart meter. Moreover, the AMI plays a vital role in collecting and transmitting energy consumption data to the utility company, and the electricity price charged against the consumed energy back to the consumers via smart meter [45]. The smart meter is a vital equipment for residential load scheduling and is installed outside of the homes between HEMC and AMI. Moreover, the smart meter is responsible for reading the energy consumption of residential buildings to be transferred to the utility company and simultaneously transferring forecasted pricing signal to HEMC in order to take part in energy management by responding to the pricing signal. In this paper, it is assumed that each home in residential buildings has three kinds of appliances: time shiftable appliances, power shiftable appliances, and critical appliances. Time shiftable appliances refer to the appliances whose operation time is schedulable, such as washing machines, cloth dryers, and water pumps. In contrast, power shiftable appliances refer to the appliances, whose power rating is flexible, such as refrigerators, air conditioners, and water dispensers. Critical appliances refer to the appliances, which are critical in nature, such as micro-waves, electric irons, and electric kettles. Both time and power shiftable appliances cause user-discomfort, while critical appliances do not cause this problem. In addition, the appliances of each home in residential buildings are assumed to be smart appliances. Each appliance has

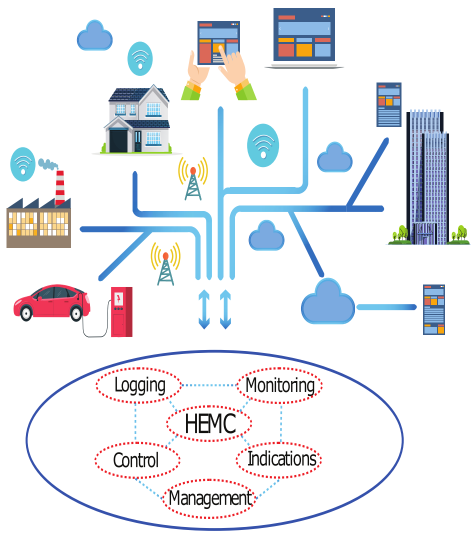

FIGURE 3. The optimal power schedule can be transmitted to each kind of appliance by HEMC via wireless network like Z-Wave, Wi-Fi, and ZigBee. The double arrow head represents bi-directional flow.

a wireless transceiver and data processor to receive and analyze the appropriate time interval. The HEMC installed in a home of residential buildings is assumed as a home gateway, which receives the forecasted DR pricing signal and energy consumption via smart meter. The communication link between HEMC, smart meter, and various appliances can be established through ICTs, such as Wi-Fi, Z-Wave, and ZegBee [19], [21], as shown in Figure 3. The appliances within the home do not interact with each other; they only interact with HEMC, as illustrated in Figures 1 and 3. The HEMC schedules the operation of all three kinds of appliances under forecasted DR pricing signal and energy consumption pattern, power availability from the utility, and consumer's priority subjected to constraints. The HEMC sends an optimal power schedule to each appliance, which is received and processed by the wireless transceiver module and data processor of appliances in order to ensure the operation according to the optimal schedule. Moreover, the HEMC specifies the starting time, power level, and type of appliance in order to control overall energy management process. The scheduling process can be either remotely monitored using mobile, tablet, or laptop or by IHD installed inside the home. Our proposed framework is mathematically modeled in the succeeding sub-section.

A. MATHEMATICAL MODEL OF THE PROPOSED FRAMEWORK

In this section, the mathematical model of the proposed framework is discussed. The utility company provides input data to ANN based forecaster, and the forecaster returns forecasted pricing signal ρ_t^f for a specific time horizon $H = \{1, 2, 3, \ldots, T\}$. The overall horizon is of 24 hours; each number in the horizon represents one hour, and $T = 24$ represents end hour of the horizon. A home in residential buildings has three kinds of appliances $A = \{A_1^T \cup A_2^P \cup A_3^C\}$: time shiftable appliances A_1^T, power shiftable appliances A_2^P, and critical appliances A_3^C; for an appliance i, α_i is the operation starting time and β_i is the operation end time. Moreover, X_i^t is the ON or OFF status indicator, r_i^t represents the number of remaining timeslots, and w_i^t represents the number of waiting timeslots. We assume energy consumption $E_i^t = 0$ for $t < \alpha_i$ and for $t > \beta_i$ because outside the scheduling time horizon $[\alpha_i, \beta_i]$, the energy is not consumed. Next, each kind of appliance can be mathematically modeled as follows:

1) TIME SHIFTABLE APPLIANCES

Time shiftable appliances have shiftable starting time and tolerate delay. These appliances can be delayed or advanced to any timeslot during scheduling time horizon. These types of appliances operate with a fixed rated power p_i^r for a specified length of operation time T_i^{lo}. The operation of such appliances can be delayed, shifted, and shut down, if required. The status of time shiftable appliances is mathematically modeled as follows:

$$\chi_i^t = \left(T_i^{lo}, \alpha_i - \beta_i - T_i^{lo} + 1\right), \tag{4}$$

$$\chi_i^{t+1} = \begin{cases} \left(r_i^t, w_i^t - 1\right) & \text{if } X_i^t = 0,\ w_i^t \geqslant 1 \\ \left(r_i^t - 1, w_i^t\right) & \text{if } X_i^t = 1,\ r_i^t \geqslant 1, \end{cases} \tag{5}$$

where Equation 4 shows the current status of time shiftable appliances and Equation 5 represents the status of time shiftable appliances in the next timeslot, respectively.

The energy consumed by the time shiftable appliances and the bill charged by the utility company against the energy consumption are formulated as follows:

$$E_i^A = \sum_{i \in A_1^T} \sum_{t=1}^{T} \left(p_i^r \times X_i^t\right), \tag{6}$$

$$C_i^A = \sum_{i \in A_1^T} \sum_{t=1}^{T} \left(p_i^r \times X_i^t \times \rho_t^f\right), \tag{7}$$

where E_i^A in Equation 6 and C_i^A in Equation 7 represent aggregated energy consumption and aggregated electricity bill, respectively.

2) POWER SHIFTABLE APPLIANCES

The power shiftable appliances operate with flexible power within the scheduling time horizon and do not work outside the scheduling time horizon. The appliances operate between the minimum $p_i^{r\,\min}$ and $p_i^{r\,\max}$ maximum rated power during the scheduling time horizon. For example, air conditioners and refrigerators regulate their power between minimum $p_i^{r\,\min}$ and $p_i^{r\,\max}$ maximum rated power. The status of power shiftable appliances can be mathematically modeled as follows:

$$\chi_i^t = \left(T_i^{lo}, \alpha_i - \beta_i - T_i^{lo} + 1\right), \tag{8}$$

$$\chi_i^{t+1} = \begin{cases} \left(r_i^t - 1, 0\right) & \text{if } X_i^t = 1,\ r_i^t \geqslant 1 \\ p_i^{r\,\min} \leqslant p_i^r \leqslant\ p_i^{r\,\max} & \text{if } X_i^t = 1,\ r_i^t \geqslant 1, \end{cases} \tag{9}$$

where Equation 8 represents the current status of power shiftable appliances and Equation 9 denotes the status of power shiftable appliances in the next timeslots.

The aggregated energy consumption of power shiftable appliances and electricity bill charged by the utility company against the energy consumption can be modeled as follows:

$$E_i^A = \sum_{i \in A_2^P} \sum_{t=1}^{T} \left(p_i^r \times X_i^t\right), \tag{10}$$

$$C_i^A = \sum_{i \in A_2^P} \sum_{t=1}^{T} \left(p_i^r \times X_i^t \times \rho_t^f\right), \tag{11}$$

where E_i^A represents the aggregated energy consumption of power shiftable appliances and C_i^A indicates the electricity bill charged by the utility company.

3) CRITICAL APPLIANCES

Critical appliances operate at fixed power ratings and cannot be interrupted and shutdown during operation until task completion. Critical appliances can be shifted and delayed before the start operation. These appliances operate during the pre-defined scheduling time horizon to decrease the user-discomfort and improve the comfort level of the residents. Mathematical modeling for the status of the critical appliances is as follows:

$$\chi_i^t = \left(T_i^{lo}, \alpha_i - \beta_i - T_i^{lo} + 1\right), \tag{12}$$

$$\chi_i^{t+1} = \begin{cases} \left(r_i^t, w_i^t - 1\right) & \text{if } X_i^t = 0,\ w_i^t \geqslant 1 \\ \left(r_i^t - 1, 0\right) & \text{if } X_i^t = 1,\ r_i^t \geqslant 1, \end{cases} \tag{13}$$

where Equation 12 indicates current status of the critical appliances and Equation 13 represents the next status of the critical appliances. The aggregated energy consumption of critical appliances and the electricity bill charged by the utility company for consumed energy is determined as follows:

$$E_i^A = \sum_{i \in A_3^C} \sum_{t=1}^{T} (p_i^r \times X_i^t), \tag{14}$$

$$C_i^A = \sum_{i \in A_3^C} \sum_{t=1}^{T} \left(p_i^r \times X_i^t \times \rho_t^f\right), \tag{15}$$

where E_i^A represents the net energy consumed by critical appliances and C_i^A in Equation 15 denotes net electricity bill charged by the utility company for using electricity. The optimal energy consumption scheduling set κ for all kinds of residential home appliances are defined as follows:

$$\begin{aligned}\kappa = \{&E/E_i^t = p_i^r,\ \forall t \in \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}\\ &\subset [\alpha_i, \beta_i],\ \forall i \in A_1^T,\\ &E_i^t = 0,\ \forall t \in H \backslash \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}, \forall i \in A_1^T,\\ &p_i^{r\,\min} \leqslant E_i^t \leqslant p_i^{r\,\max},\ \forall t \in [\alpha_i, \beta_i],\ \forall i \in A_2^P,\\ &E_i^t = 0,\ \forall t \in H\backslash[\alpha_i, \beta_i],\ \forall i \in A_2^P,\\ &E/E_i^t = p_i^r,\ \forall t \in T_i^{lo} \subset [\alpha_i, \beta_i],\ \forall i \in A_3^C,\\ &E_i^t = 0,\ \forall t \in T_i^{lo}\backslash[\alpha_i, \beta_i],\ \forall i \in A_3^C\}. \end{aligned} \tag{16}$$

The optimal scheduling set κ depends on the price forecasted by ANN and the control parameters of the appliances such as α_i, β_i, T_i^{lo}, p_i^r, $p_i^{r\,\max}$, and $p_i^{r\,\min}$.

IV. PROBLEM FORMULATION

The HEMC based on DA-GmEDE receives the forecasted pricing signal and publishes this pricing signal to the consumers ahead of time. The consumers send their power usage pattern to the HEMC based on DA-GmEDE strategy. The HEMC tries to manage the consumers' power usage in such a manner that their electricity bill is minimized, PAR is reduced, and the desired trade-off between electricity bill and discomfort is achieved. However, it is difficult to achieve all these objectives at the same time because these are conflicting parameters and trade-offs exist in their nature. For example, in case of time shiftable appliances, if the consumers select $\alpha_i = 10am$ and $\beta_i = 1pm$ for a washing machine to finish washing before afternoon, the HEMC based on DA-GmEDE strategy postpones their operation to $\alpha_i = 5pm$ and $\beta_i = 9pm$ to reduce their electricity bill; however, the consumers will face discomfort due to postponed operation of the washing machine. For shiftable appliances, the HEMC based on DA-GmEDE strategy regulates the operation between the $p_i^{r\,\min}$ and $p_i^{r\,\max}$ in order to reduce the electricity bill. This reduced electricity bill also results in user-discomfort. The HEMC based on DA-GmEDE strategy tries to acquire the desired tradeoff between the electricity bill and user-discomfort. Thus, the proposed objective function is modeled as a minimization function for the purpose of minimizing the electricity expense, PAR, and user-discomfort. First, each objective function, i.e., electricity bill, PAR, and user-discomfort are formulated individually. Then, the overall residential load scheduling problem is formulated.

Since the forecasted pricing signal is known ahead of time to the consumers, therefore, the overall electricity bill of all appliances within a home during the scheduling time horizon can be determined as follows:

$$C_i^A = \sum_{i \in A} \sum_{t=1}^{T} \left(p_i^r \times X_i^t \times \rho_t^f\right). \tag{17}$$

The user-discomfort caused by delaying or advancing the operation of time shiftable appliances can be modeled as follows:

$$d_t^{A_1^T}(F_i^t) = \lambda_i\left(F_i^t - \alpha_i\right)^n, \tag{18}$$

where $0 < \lambda_i < 1$ and $n \geqslant 1$ represents operation characteristics of time shiftable appliances. The user-discomfort caused by power shiftable appliances is due to the power deviation from the rated power, which can be modeled as follows:

$$d_p^{A_2^P}(E_i^t) = \omega_i^t\left(E_i^t - \hat{E}_i^t\right)^2, \tag{19}$$

where ω_i^t varies parameter with respect to timeslots t and $\hat{E}_i^t$ is the normal power consumption. Moreover, $d_p^{A_2^P} = 0$ at $E_i^t = \hat{E}_i^t$ for $t \in H \backslash[\alpha_i, \beta_i]$. This quadratic function is minimum at $E_i^t = \hat{E}_i^t$ and increases as the deviation of E_i^t increases from $\hat{E}_i^t$. The functional failure of the appliance can occur at two extremes of deviation $\hat{E}_i^t \pm \Delta$. Thus, some counter measure must be taken to overcome these failures. The counter measure at extreme $\hat{E}_i^t + \Delta$ or extreme $\hat{E}_i^t - \Delta$ is ς.

The critical appliances do not cause any user-discomfort because neither power nor time can be changed or delayed during the operation until the task completion. Thus, critical appliances contribute to improve the comfort level of the consumers. The net user-discomfort caused by both time shiftable appliances and power shiftable appliances in a home can be modeled as follows:

$$d_i^A = \sum_{i \in A_1^T} \lambda_i\left(F_i^t - \alpha_i\right)^n + \sum_{t} \sum_{i \in A_2^P} d_p^{A_2^P}(E_i^t). \tag{20}$$

The overall PAR for all appliances within a home during the scheduling time horizon can be modeled as follows:

$$R_A^P = \frac{\max(E_i^t)}{\frac{1}{T}\sum_{t=1}^{T}\sum_{i=}^{A}(E_i^t)}, \tag{21}$$

where R_A^P represents the PAR, which is one of our objectives.

Now, the overall residential load scheduling is formulated as a minimization problem as:

$$\begin{aligned}&\min\ \left(\gamma_1 C_i^A + \gamma_2 R_A^P + \gamma_3 d_i^A\right)\\ &\quad E/E_i^t = p_i^r, \quad \forall t \in \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}\\ &\quad \subset [\alpha_i, \beta_i], \quad \forall i \in A_1^T,\end{aligned}$$

$$
\begin{aligned}
&E_i^t = 0, \quad \forall t \in H \backslash \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}, \forall i \in A_1^T, \\
&p_i^{r\,\min} \leqslant E_i^t \leqslant p_i^{r\,\max}, \quad \forall t \in [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&E_i^t = 0, \quad \forall t \in H \backslash [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&E/E_i^t = p_i^r, \quad \forall t \in T_i^{lo} \subset [\alpha_i, \beta_i],\ \forall i \in A_3^C, \\
&E_i^t = 0, \quad \forall t \in T_i^{lo} \backslash [\alpha_i, \beta_i],\ \forall i \in A_3^C\}, \\
\text{variables } & F_i^t \ (i \in A_1^T,\ t \in H), \\
& E_i^t \ (i \in A_2^P,\ t \in H), \\
& p_i^r \ (i \in A_3^C), \qquad (22)
\end{aligned}
$$

where C_i^A is modeled in Equation 17, R_A^P is modeled in Equation 21, and d_i^A is modeled in Equation 20, respectively. Parameters γ_1, γ_2, and γ_3 are weights used to obtain desired trade-off between conflicting parameters of the objective function.

Now, the consumers operation modes based on their priority, preferences, and with respect to the objective function are defined and modeled in the succeeding subsections. There are four types of operation modes of consumers, each of which is defined and modeled as follows:

4) CONSUMERS MODE I

In this mode of operation, the focus of consumers is on reducing their electricity bill even if it results in high user-discomfort. Thus, HEMC will adjust weights of the objective function such as ($\gamma_1 = 1, \gamma_2 = 0, \gamma_3 = 0$) to achieve consumers' priority and preference. For consumers mode 1, the optimization problem can be modified as follows:

$$
\begin{aligned}
&\min \sum_{i \in A} \sum_{t=1}^{T} \left(p_i^r \times X_i^t \times \rho_t^f\right) \\
&\text{sub. to: } E/E_i^t = p_i^r, \quad \forall t \in \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\} \\
&\qquad \subset [\alpha_i, \beta_i], \quad \forall i \in A_1^T, \\
&\qquad E_i^t = 0, \quad \forall t \in H \backslash \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}, \forall i \in A_1^T, \\
&\qquad p_i^{r\,\min} \leqslant E_i^t \leqslant p_i^{r\,\max}, \quad \forall t \in [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&\qquad E_i^t = 0, \quad \forall t \in H \backslash [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&\qquad E/E_i^t = p_i^r, \quad \forall t \in T_i^{lo} \subset [\alpha_i, \beta_i],\ \forall i \in A_3^C, \\
&\qquad E_i^t = 0, \quad \forall t \in T_i^{lo} \backslash [\alpha_i, \beta_i],\ \forall i \in A_3^C\}, \\
&\text{variables } F_i^t \ (i \in A_1^T,\ t \in H), \\
&\qquad E_i^t \ (i \in A_2^P,\ t \in H), \\
&\qquad p_i^r \ (i \in A_3^C). \qquad (23)
\end{aligned}
$$

5) CONSUMERS MODE II

In this mode of operation, consumers prefer comfort even at the cost of higher electricity bills. The HEMC adjusts weights ($\gamma_1 = 0, \gamma_2 = 0, \gamma_3 = 1$) of the optimization problem such that the priority of mode II consumers is imposed. The optimization problem is modified and can be modeled as follows:

$$
\begin{aligned}
&\min \sum_{i \in A_1^T} \lambda_i \left(F_i^t - \alpha_i\right)^n + \sum_{t} \sum_{i \in A_2^P} d_p^{A_2^P}(E_i^t) \\
&\text{sub. to: } E/E_i^t = p_i^r, \quad \forall t \in \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\} \\
&\qquad \subset [\alpha_i, \beta_i], \quad \forall i \in A_1^T, \\
&\qquad E_i^t = 0, \quad \forall t \in H \backslash \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}, \forall i \in A_1^T, \\
&\qquad p_i^{r\,\min} \leqslant E_i^t \leqslant p_i^{r\,\max}, \quad \forall t \in [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&\qquad E_i^t = 0, \quad \forall t \in H \backslash [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&\qquad E/E_i^t = p_i^r, \quad \forall t \in T_i^{lo} \subset [\alpha_i, \beta_i],\ \forall i \in A_3^C, \\
&\qquad E_i^t = 0, \quad \forall t \in T_i^{lo} \backslash [\alpha_i, \beta_i],\ \forall i \in A_3^C\}, \\
&\text{variables } F_i^t \ (i \in A_1^T,\ t \in H), \\
&\qquad E_i^t \ (i \in A_2^P,\ t \in H), \\
&\qquad p_i^r \ (i \in A_3^C). \qquad (24)
\end{aligned}
$$

6) CONSUMERS MODE III

In mode III, the focus of consumers is on reducing PAR, which is favorable for both consumers and the utility company. The reduced PAR smoothens out the demand curve, which eases the burden on the utility company by turning off peak power plants thereby decreasing burden on consumers via reduced price per unit of the energy consumption. The HEMC adjusts weights ($\gamma_1 = 0, \gamma_2 = 1, \gamma_3 = 0$) so as to obtain the reduced PAR. The modified optimization problem for mode III can be modeled as follows:

$$
\begin{aligned}
&p_i^r \ (i \in A_3^C) \\
&\min \ \frac{\max(E_i^t)}{\frac{1}{T} \sum_{t=1}^{T} \sum_{i=}^{A} (E_i^t)} \\
&\text{sub. to: } E/E_i^t = p_i^r, \ \forall t \in \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\} \\
&\qquad \subset [\alpha_i, \beta_i], \quad \forall i \in A_1^T, \\
&\qquad E_i^t = 0, \quad \forall t \in H \backslash \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}, \forall i \in A_1^T, \\
&\qquad p_i^{r\,\min} \leqslant E_i^t \leqslant p_i^{r\,\max}, \quad \forall t \in [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&\qquad E_i^t = 0, \quad \forall t \in H \backslash [\alpha_i, \beta_i],\ \forall i \in A_2^P, \\
&\qquad E/E_i^t = p_i^r, \quad \forall t \in T_i^{lo} \subset [\alpha_i, \beta_i],\ \forall i \in A_3^C, \\
&\qquad E_i^t = 0, \quad \forall t \in T_i^{lo} \backslash [\alpha_i, \beta_i],\ \forall i \in A_3^C\}, \\
&\text{variables } F_i^t \ (i \in A_1^T,\ t \in H), \\
&\qquad E_i^t \ (i \in A_2^P,\ t \in H), \\
&\qquad p_i^r \ (i \in A_3^C). \qquad (25)
\end{aligned}
$$

7) CONSUMERS MODE IV

In mode IV, the consumers care about all the three objectives: reduced electricity bill, alleviated PAR, and achieving the desired trade-off between the electricity bill and user-discomfort. The HEMC will assign equal weights to ($\gamma_1 = 1/3, \gamma_2 = 1/3, \gamma_3 = 1/3$) for the purpose of achieving all the objectives. The optimization problem for mode IV can be written as follows:

$$\begin{aligned}
&\min \left(\frac{1}{3}C_i^A + \frac{1}{3}R_A^P + \frac{1}{3}d_i^A\right) \\
&\text{sub. to: } E/E_i^t = p_i^r, \quad \forall t \in \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\} \\
&\qquad \subset [\alpha_i, \beta_i], \quad \forall i \in A_1^T, \\
&\qquad E_i^t = 0, \quad \forall t \in H \setminus \left\{F_i^t, \ldots, F_i^t + T_i^{lo} - 1\right\}, \forall i \in A_1^T, \\
&\qquad p_i^{r\,\min} \leqslant E_i^t \leqslant p_i^{r\,\max}, \quad \forall t \in [\alpha_i, \beta_i], \ \forall i \in A_2^P, \\
&\qquad E_i^t = 0, \quad \forall t \in H \setminus [\alpha_i, \beta_i], \ \forall i \in A_2^P, \\
&\qquad E/E_i^t = p_i^r, \quad \forall t \in T_i^{lo} \subset [\alpha_i, \beta_i], \ \forall i \in A_3^C, \\
&\qquad E_i^t = 0, \quad \forall t \in T_i^{lo} \setminus [\alpha_i, \beta_i], \ \forall i \in A_3^C\}, \\
&\text{variables } F_i^t \ (i \in A_1^T, \ t \in H), \\
&\qquad E_i^t \ (i \in A_2^P, \ t \in H), \\
&\qquad p_i^r \ (i \in A_3^C).
\end{aligned} \tag{26}$$

V. PROPOSED AND ADOPTED STRATEGIES

Traditional strategies such as analytical model based strategies, heuristic algorithms based strategies, and game theory based strategies are capable of performing energy management by scheduling residential loads. However, these strategies are not able to handle a large number of residential home appliances and are not efficient for performing real-time optimization due to their deterministic nature and inherent limitations. Therefore, a strategy based on DA-GmEDE algorithm is developed for efficient energy management of residential buildings. The proposed algorithm is a hybrid of grey wolf optimization (GWO) algorithm and modified enhanced differential evolution (mEDE) algorithm, named GmEDE algorithm. The proposed algorithm takes the best features of both the algorithms. The detailed description is as follows:

A. GREY WOLF OPTIMIZATION ALGORITHM

GWO is a heuristic algorithm inspired by hunting and hierarchical leadership nature of wolves. The wolves have three leadership levels: alpha α, beta β, and delta δ. The α is assumed as the best leader of the group, which is responsible for the guidance of other wolves. The γ is the weakest member of the group. The β and δ come after α in the hierarchical order. The γ will not be considered for the leadership of wolves. In our scenario, α is considered as the best/fittest member to acquire one of our objectives, i.e., electricity bill minimization. Initially, the population is generated randomly by Equation 27 as follows:

$$Z(a, b) = rand(popl, A), \tag{27}$$

where *popl* is the grey wolves population and A is the set of appliances in a home of residential buildings. The GWO has three main phases: (i) encircling prey, (ii) hunting, and (iii) grey wolves position update. The step-by-step procedure of GWO algorithm is depicted in Algorithm 1.

Algorithm 1 Pseudo Code of the Grey Wolf Optimization Algorithm

```
Parameters initialization Mitr, popl, A, α, β, δ;
Randomly population generation of grey wolves
Z_a(a = 1, 2, 3, ..., n);
Z(a, b) = rand(popl, A);
while itr < Mitr do
    for a = 1:popl do
        Determine the fitness as objective function using
        Equation (Fit = p_i^r × X_i^t);
        if fit < α_scre then
            α_scre = fit;
            α_pos = Z(a, :);
        end
        if fit > α_scre and fit< β_scre then
            β_scre = fitness;
            β_pos = Z(a, :);
        end
        if fit > α_scre and fit> β_scre and fit< δ_scre then
            δ_scre = fit;
            δ_pos = Z(a, :);
        end
    end
    for a = 1:popl do
        for b = 1:A do
            Create r_1 and r_2 using rand command;
            Determine both D and B fitness coefficients
            using Equations (D⃗ = 2 a⃗ × r_1 − a⃗) and
            (B⃗ = 2 × r⃗_2);
            Update α, β, and δ by
            Equations (A⃗_α = B⃗_1 × x⃗_α − x⃗),
            (A⃗_β = B⃗_2 × x⃗_β − x⃗), and
            (A⃗_δ = B⃗_3 × x⃗_δ − x⃗);
        end
    end
end
```

B. MODIFIED ENHANCED DIFFERENTIAL EVOLUTION ALGORITHM

The modified enhanced differential evolution (mEDE) is an updated and modified version of DE and EDE. It is a population based algorithm developed by Storn and Price in 1995 [47]. The mEDE has three main steps: mutation, crossover, and selection. First, the population is randomly generated by Equation 28 as follows:

$$Z(a, b) = l_b + (rand \times (U_b - l_b)). \tag{28}$$

Then the mutation is performed on the population, which is randomly generated in the former step. Three random vectors are chosen during the mutation process for each target vector. To form a mutant vector, the difference of two vectors is added into the third vector. The mutant vector is generated using Equation 29 as follows:

$$V_{a,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}), \tag{29}$$

where x_{r1}, x_{r2}, x_{r3} and F represent the three random vectors and scaling factor, respectively. Target vector is the first vector among the selected vectors. After the mutant vector generation phase, the crossover phase starts, where the trial vector is generated by combining the target and mutant vector elements on the basis of crossover rate, which decides how many elements are taken from target and mutant vectors. After the trial vector is created, the trial and target vectors are compared in order to select the best vector with better fitness for the purpose of updating the generation. The mEDE has easy implementation as compared to DE because the DE has three control parameters (population size, scaling factor, and crossover rate) whereas mEDE has only two (population size and scaling factor). In mEDE, all the initial phases are the same as DE; the difference is only in the crossover rate, and five trial vectors are generated instead of one. The five trial vectors are generated using Equations 30-34:

$$U_{b,a,G+1} = \begin{cases} V_{b,a,G+1} & if\ rand(b) \leq 0.30 \\ x_{b,a,G+1} & Otherwise \end{cases} \tag{30}$$

$$U_{b,a,G+1} = \begin{cases} V_{b,a,G+1} & if\ rand(b) \leq 0.60 \\ x_{b,a,G+1} & Otherwise \end{cases} \tag{31}$$

$$U_{b,a,G+1} = \begin{cases} V_{b,a,G+1} & if\ rand(b) \leq 0.90 \\ x_{b,a,G+1} & Otherwise \end{cases} \tag{32}$$

$$U_{b,a,G+1} = randb(j) \cdot x_{b,a,G+1} \tag{33}$$

$$U_{b,a,G+1} = rand(b) \cdot v_{b,a,G} + (1 - randb(b)) \cdot x_{b,a,G} \tag{34}$$

The step-by-step procedure of mEDE algorithm is depicted in Algorithm 2.

C. PROPOSED GREY WOLF MODIFIED ENHANCED DIFFERENTIAL EVOLUTION ALGORITHM

The grey wolf modified enhanced differential evolution (GmEDE) algorithm is our proposed algorithm, which is a hybrid of GWO and mEDE algorithm. The proposed algorithm takes the best features of both GWO and mEDE algorithms to optimally schedule the load of residential buildings. In mEDE, the population is created in four phases: initialization of parameters, mutation, crossover, and best trial vector selection. Randomly generated population is then updated with the fittest trial vector, which is created by comparing with the target vector. Adopted selection procedure is better because a trial vector with best fitness is considered for the selection process. The GWO has three main phases: (i) encircling prey, (ii) hunting, and (iii) position update of wolves. The agents update positions w.r.t. the leader (α) within the pack. There is no mechanism for comparison among α, β, and δ in GWO to search the best agent selection. There is a possibility that α and δ may be close enough to the prey as compared to α. Thus, the crossover phase of mEDE is performed for clear comparison among the search agents of GWO. After the best agent selection, the position is updated in GWO. The crossover operation on α, β, and δ is performed

Algorithm 2 Pseudo Code of Modified Enhanced Differential Evolution Algorithm

```
Parameters initialization Mitr, R, popl, t;
Population generation using
Equation (Z(a, b) = l_b + (rand × (U_b − l_b))) ;
for t = 1:T do
    Determine the mutant vector using
    Equation (V_{a,G+1} = x_{r1,G} + F(x_{r2,G} − x_{r3,G}));
    for itr = 1:Mitr do
        Determine the 1st trial vector with R 0.30;
        if rand ≤ 0.30 then
            μ_b = υ_b
            else
            μ_b = x_b
        end
        Determine the 2nd trial vector with R 0.60;
        if rand ≤ 0.60 then
            μ_b = υ_b
            else
            μ_b = x_b
        end
        Determine the 3rd trial vector with R 0.90;
        if rand ≤ 0.90 then
            μ_b = υ_b
            else
            μ_b = x_b
        end
        Determine the 4th and 5th trial vectors by
        Equations (33) and (34), respectively;
        Determine the best fittest trial vector ;
        Z_new ← μ_b best;
        Compare trial vector with target vector to
        generate best vector;
        if f(Z_new) < f(Z_b) then
            Z_b = Z_new
        end
    end
end
```

using the following Equations:

$$\alpha_{new} = \begin{cases} v_b & \text{if fitness of } v_b \leqslant \alpha \\ \alpha & \text{Otherwise} \end{cases} \tag{35}$$

$$\beta_{new} = \begin{cases} v_b & \text{if fitness of } v_b \leqslant \beta \\ \beta & \text{Otherwise} \end{cases} \tag{36}$$

$$\delta_{new} = \begin{cases} v_b & \text{if fitness of } v_b \leqslant \delta \\ \delta & \text{Otherwise} \end{cases} \tag{37}$$

The steps of the proposed GmEDE algorithm are the following: (i) initialization of parameters, (ii) encircling prey, (iii) best search agent selection, and (iv) position update. The step-by-step procedure of the proposed GmEDE is presented in Algorithm 3

Algorithm 3 Pseudo Code of Our Proposed Grey Wolf Modified Enhanced Differential Evolution algorithm

```
Parameters initialization Mitr, popl, A, α, β, δ;
Initially randomly generate grey wolves population Z_a(a = 1, 2, 3, ..., n);
Z(a, b) = rand(popl, A);
while itr < Mitr do
    for a = 1:popl do
        Determine a mutant vector using Equation (V_{a,G+1} = x_{r1,G} + F(x_{r2,G} − x_{r3,G})) from mEDE;
        Determine the fitness of mutant vector as cost × υ_b;
        Generate randomly α, β, δ;
        Determine the fitness of α, β, andδ as the objective function using Equation (Fitness = p_i^r × X_i^t);
        if fit of υ(b) < α_scre then
            α_pos = υ_b;
        end
        if fitυ_b > α_scre and υ_b < β_scre then
            β_pos = υ(b);
        end
        if fit x_b > α_scre and fit x_b > β_scre and fit x_b < δ_scre then
            δ_pos = υ_b);
        end
    end
    for a = 1:popl do
        for b = 1:A do
            Randomly create r_1 and r_2 having values 0<r<1;
            Determine the fitness of both D and B coefficients by Equations (D⃗ = 2 a⃗ × r_1 − a⃗) and (B⃗ = 2 × r⃗_2);
            Update α, β, δ using Equations (A⃗_α = B⃗_1 × x⃗_α − x⃗), A⃗_β = B⃗_2 × x⃗_β − x⃗, and A⃗_δ = B⃗_3 × x⃗_δ − x⃗);
        end
    end
end
```

VI. SIMULATION RESULTS AND DISCUSSION

In this section, the simulation results and discussion are presented to validate the performance of the proposed energy management strategy with day-ahead DR price signal and energy consumption forecast using ANN. In this paper, residential buildings having three kinds of appliances: time shiftable appliances, power shiftable appliances, and critical appliances. The parameters of the algorithms used in the simulation and description of all the appliances in residential buildings are listed in Table 2 and Table 3, respectively. The parameters (power rating, operation timeslots, actual energy consumption, etc.) of the home appliances are adopted from reference [48]. The scheduling time horizon is of twenty-four hours, starting from 01:00am to 00:59am. The day-ahead DR pricing signal is obtained from the report of MISO, which is taken from the FERC [44]. The ANN is enabled by learning to forecast the day-ahead prices for HEMC to optimally schedule the home appliances within the scheduling time horizon subjected to power system stability, reliability, and security. The forecasted day-ahead DR pricing signal and energy consumption patterns are depicted in Figures 4 and 5, respectively. The HEMC is based on our proposed DA-GmEDE and existing (DA-GA, DA-game-theoretic) strategies. Our proposed DA-GmEDE based scheduling strategy is compared with W/O (without) scheduling and scheduling based on existing strategies: DA-GA [18], [19] and DA-game-theoretic [37] to validate the superiority of the proposed strategy. For fair comparison,

TABLE 2. Parameters used in simulation for the proposed and existing energy management strategies.

Parameters	Values
Population	100
Minimum lower population bound	0.1
Maximum upper population bound	0.9
Number of wolves in each pack	17
Maximum epochs	100
Decision variables	2
Learning rate	0.002
Weight decay	0.0002
Initial value of weights	0.1
Initial value of bias	0
Number of objectives	2
Momentum	0.5
Features selection threshold	0.5
Distance from prey	Varies
Status of leader	0 or 1
Number of dimensions	17
Gradient of problem	Varies

TABLE 3. Parameters of residential home appliances used in simulations.

Classification	Types of appliances	Power rating (kW)	Operation timeslots (Hours)	Priority
Power shiftable appliances	Air conditioner	[0.8 1.5]	12	2
	Refrigerator	[0.5 1.2]	24	
	Water dispenser	[0.8 1.2]	24	
	Electric radiator	[0.5 1.5]	10	
Time shiftable appliances	Washing machine	0.7	5	3
	Cloth dryer	2	4	
	Water pump	0.4	2	
Critical appliances	Electric kettle	1.5	1	1
	Electric iron	1.8	4	
	Microwave	1.8	3	
	Hair dryer	1.2	1	

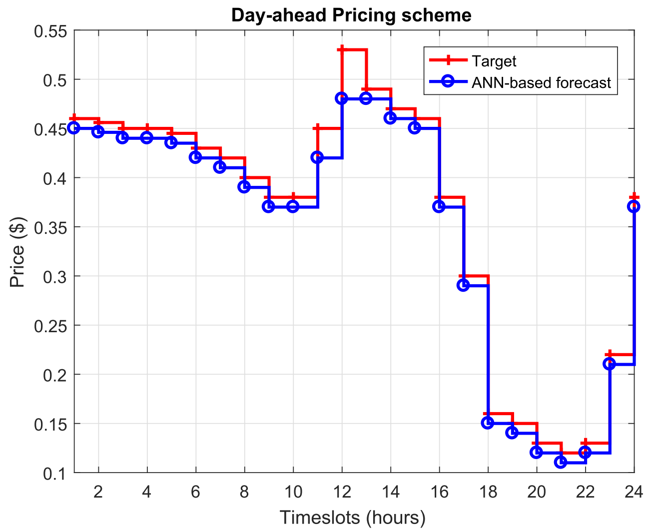

FIGURE 4. Forecasted day-ahead DR pricing signal using ANN.

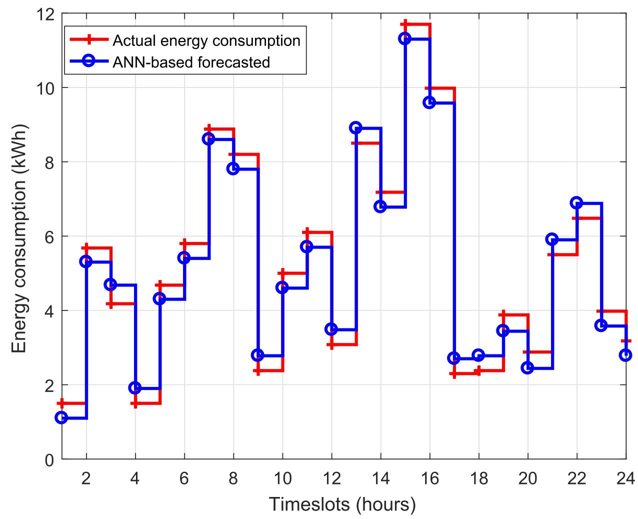

FIGURE 5. Forecasted day-ahead home energy consumption pattern using ANN.

we have used day-ahead forecasted DR pricing signal and energy consumption pattern, and the same set of appliances as listed in Table 3 for our proposed DA-GmEDE strategy and existing strategies (DA-GA, and DA-game theoretic). The proposed DA-GmEDE based strategy and existing strategies (DA-GA, DA-game-theoretic) are tested via performance metrics like electricity cost, PAR, and trade-off between electricity bill and user-discomfort. The detailed description is as follows:

A. ENERGY CONSUMPTION AND ELECTRICITY BILL UNDER FOUR MODES OF OPERATION

The energy consumption and electricity cost for four operation modes are illustrated in Figures 6 and 7, respectively. It is depicted in Figure 6 that energy consumption of residential buildings within the scheduling time horizon under the operation mode IV is higher than that of modes I and III, and lower than that of operation mode II. The peak energy consumption of operation mode I, mode III, and mode IV is much lower than that of operation mode II. This behavior is due to the fact that users under operation mode II care more about their comfort even at high energy consumption. The energy consumption of consumers under operation mode III is higher than that of operation mode I, and lower than that of operation mode II and mode IV because the user under operation mode III only cares about PAR. The energy consumption of users under operation mode I is lower than that of all modes II, III, and IV because users under operation mode I want to reduce electricity bill even at the cost of high user-discomfort. Figure 7 illustrates that electricity bill per hour within the scheduling time horizon under operation modes I, III, and IV is lower than that under operation mode II because the appliances under operation modes I, III, and IV postpone their operation either in terms of time or power. Thus, the HEMC based on DA-GmEDE achieves the desired trade-off between the electricity bill payment and discomfort.

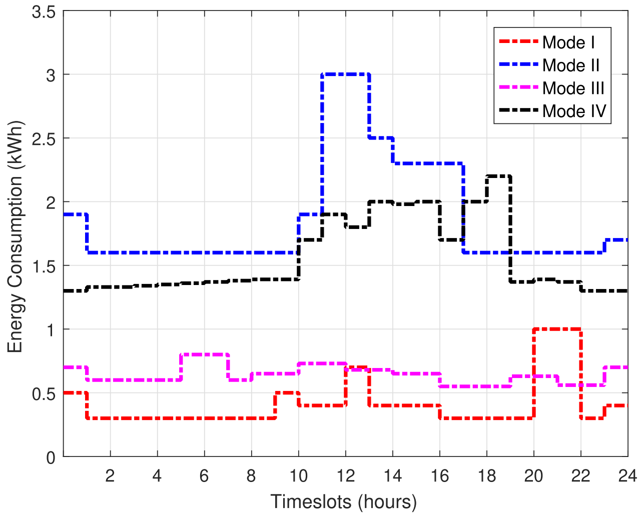

FIGURE 6. Evaluation of energy consumption under four modes operation with forecasted day-ahead pricing signal.

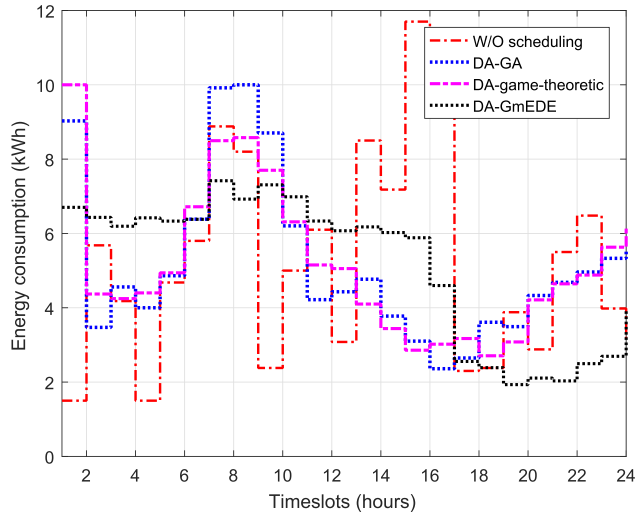

FIGURE 8. Comparison of energy consumption per hour without load scheduling and with load scheduling based on DA-GmEDE, DA-GA, and DA-game-theoretic using forecasted day-ahead pricing signal.

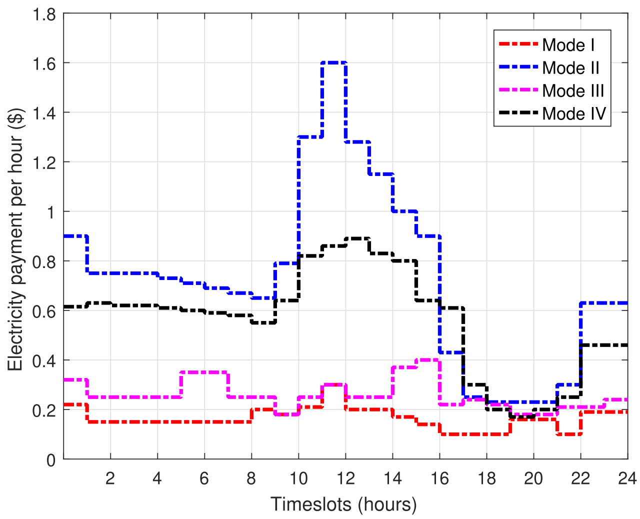

FIGURE 7. Evaluation of electricity bill payment under four modes of operation with forecasted day-ahead pricing signal.

Furthermore, the HEMC reduced both electricity bill and PAR.

B. ENERGY CONSUMPTION OF A HOME IN RESIDENTIAL BUILDINGS WITHIN THE SCHEDULING TIME HORIZON

The energy consumption pattern of a home before scheduling and after scheduling with DA-GA, DA-game-theoretic, and our proposed DA-GmEDE strategies are illustrated in Figure 8. The energy consumption of a home before scheduling is high during 6 to 9 and 13 to 17 hours, which are the peak demand hours leading to high electricity bill and PAR. The energy consumption of a home after scheduling with DA-GA, DA-game-theoretic, and our proposed DA-GmEDE strategies are limited to 7 kWh, 8.24 kWh, and 8.14 kWh, respectively. The DA-GA and DA-game-theory based strategies schedule energy consumption during 7 to 10 hours is 9 kWh, which is very high because critical appliances are scheduled in these timeslots. The DA-GA and DA-game-theory based strategies have moderate energy consumption in the remaining timeslots. The proposed DA-GmEDE based strategy for residential buildings has the energy consumption of 7 kWh during 7 to 10 hours, which is the peak energy consumption, and is less as compared to peak energy consumption of both DA-GA and DA-game-theory based strategies. The proposed DA-GmEDE based strategy has moderate energy consumption in the remaining timeslots. Thus, it is concluded that our proposed strategy is 36.4% better than W/O scheduling case, and 33.3% better than both DA-GA and DA-game-theory based scheduling. Thus, our proposed DA-GmEDE strategy outperforms the existing strategies because the DA-GmEDE has the most suitable and optimal load profile as compared to other strategies.

C. ELECTRICITY BILL PER HOUR OF A HOME IN RESIDENTIAL BUILDINGS WITHIN SCHEDULING TIME HORIZON

The daily electricity bill of home appliances with scheduling based on our proposed DA-GmEDE, DA-GA, DA-game-theoretic, and W/O scheduling is illustrated in Figure 9. Before scheduling, the electricity bill is high during 6 to 9 and 13 to 17 hours because consumers use more appliances during these peak hours, which leads to higher electricity bill of \$5.5. After scheduling the residential home appliances with DA-GmEDE, DA-GA, and DA-game-theory based strategies, a reduction is achieved in electricity bill per timeslot up to \$0.7, \$1.2, and \$0.9, respectively. The maximum electricity bill is \$5.5 per timeslot, which is reduced to: \$0.7 with our proposed DA-GmEDE, \$1.2 with DA-GA, and \$0.9 with DA-game-theoretic. It is obvious that each strategy has the capability to schedule the residential load, which leads to reduced electricity bill as compared to W/O scheduling case. Our proposed DA-GmEDE based strategy outperforms

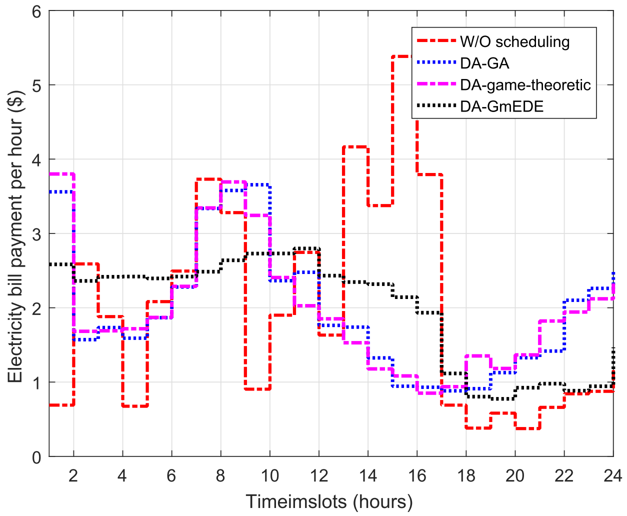

FIGURE 9. Comparison of electricity bill payment per hour without load scheduling and with load scheduling based on DA-GmEDE, DA-GA, and DA-Game-theory under forecasted day-ahead pricing signal.

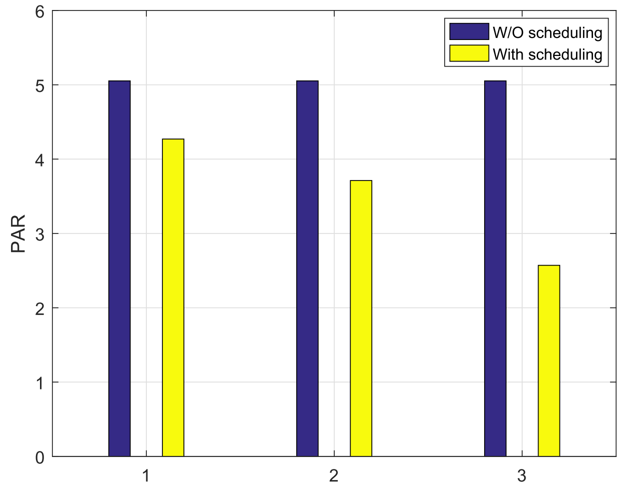

FIGURE 10. Comparison of PAR without load scheduling and with load scheduling based on DA-GA, DA-Game-theory, and DA-GmEDE, respectively, under forecasted day-ahead pricing signal.

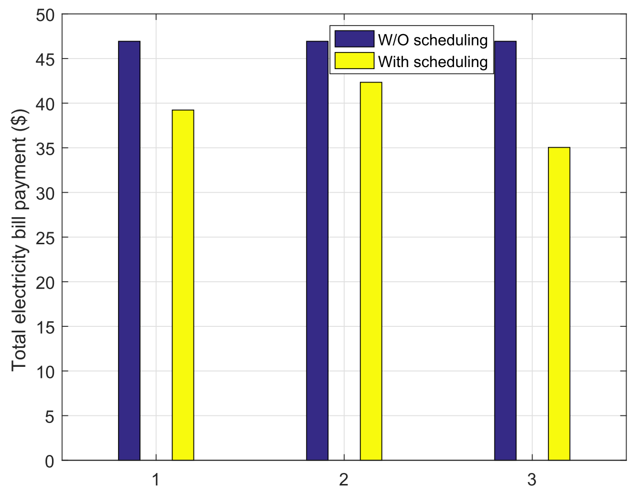

FIGURE 11. Total electricity bill payment without load scheduling and with load scheduling based on DA-GA, DA-Game-theory, and DA-GmEDE, respectively, under forecasted day-ahead pricing signal.

DA-GA based strategy by 41.6% and DA-game-theoretic strategy by 22.2% in terms of electricity bill reduction. Thus, extensive simulation results depict that our proposed DA-GmEDE based strategy achieves significant reduction in electricity bill compared to other existing strategies.

D. EVALUATION OF PAR BEFORE AND AFTER LOAD SCHEDULING OF A HOME

The evaluation of PAR W/O scheduling and with scheduling based on DA-GA, DA-game-theoretic, and our proposed DA-GmEDE based strategies are illustrated in Figure 10. The emphasis of PAR is to maintain balanced energy consumption during the scheduling time horizon, which is favorable for both the utility company and the end users in terms of power system stability and cost reduction, respectively. The HEMC based on DA-GA, DA-game-theoretic, and our proposed DA-GmEDE based strategies shift the load from high price hours to low price hours under day-ahead pricing signal, which leads to reduction in PAR. The load scheduled based on DA-GA, DA-game-theoretic, and DA-GmEDE based strategies reduce the PAR as compared to W/O scheduling case by 17.64%, 25.49%, 47.05%, respectively. The percent reduction of the proposed DA-GmEDE based strategy is more compared to the other strategies, as illustrated in Figure 10. Hence, it is concluded that our proposed DA-GmEDE based strategy outperforms other strategies in terms of PAR.

E. TOTAL ELECTRICITY BILL OF A HOME BEFORE AND AFTER SCHEDULING

The evaluation of total electricity bill payment W/O scheduling and with scheduling based on DA-GA, DA-game-theoretic, and our proposed DA-GmEDE based strategies is illustrated in Figure 11. The overall electricity bill reduction of DA-GA, DA-game-theoretic, and our proposed DA-GmEDE based strategy is 15.2%, 8.7%, and 23.9%, respectively, compared to the unscheduled case. The net bill reduction of the proposed DA-GmEDE is high compared to the other strategies. Hence, our proposed strategy outperforms the existing strategies in terms of both electricity bill payment and PAR.

F. ANALYSIS OF PERFORMANCE TRADE-OFF

The performance trade-off between our proposed DA-GmEDE strategy and existing (DA-GA, and DA-game-theoretic) strategies in terms of electricity bill and waiting time is illustrated in Figure 12. In energy management, the trade-off exists between electricity cost and discomfort. The users whose focus is on electricity bill minimization will have to wait for low price hours to operate an appliance. Thus, there is an inverse relationship between the electricity bill and user-discomfort. In W/O scheduling scenario,

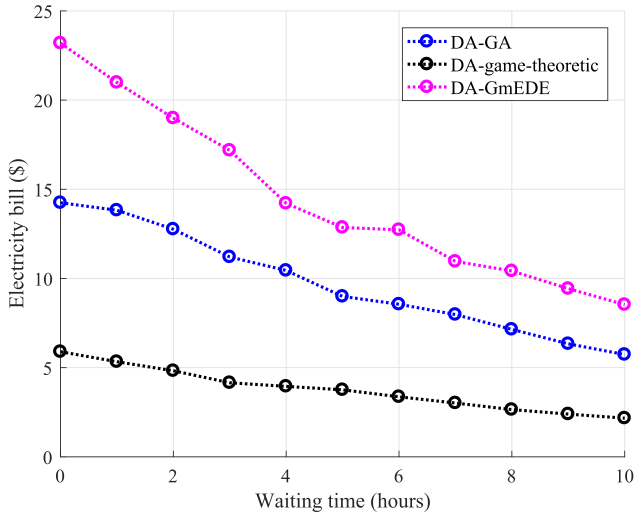

FIGURE 12. **Evaluation of performance trade-off between electricity bill and waiting time of the proposed DA-GmEDE strategy and existing DA-GA and DA-Game-theoretic strategies.**

the waiting time is zero because users operate appliances according to their choice and demand. However, for the scheduled energy consumption pattern based on our proposed DA-GmEDE strategy and existing DA-GA, and DA-game-theory based strategies, it must compromise on their comfort. Users face increased discomfort when the difference between users' preferred time and scheduled time is high. The performance trade-off between the electricity bill and waiting time is high for DA-GA and DA-game-theory based strategies. On the other hand, for our proposed DA-GmEDE strategy, the performance trade-off between the electricity bill and user-discomfort is comparatively minimum. Thus, our proposed GmEDE based strategy achieves the desired trade-off between the electricity bill and user-discomfort.

VII. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In this paper, a framework based on HEMC is proposed and then a strategy based on DA-GmEDE is presented for HEMC to perform efficient energy management of residential buildings under the forecasted day-ahead DR pricing signal and consumer preferences. Furthermore, the energy management problem is formulated as an optimization problem using four modes of operation to achieve the optimal energy consumption schedule and to achieve the desired trade-off between electricity bill and user-discomfort. The proposed framework is favorable for both consumers and power companies. For consumers, the proposed DA-GmEDE based strategy schedules the home appliances to maximize the benefit in terms of reduced electricity bill. On the other hand, the benefit achieved for the utility companies is the reduction of PAR, which increases the stability of the power system by smoothing the demand curve. For performance validation, simulations were carried out and results of the proposed framework based on DA-GmEDE were compared with DA-GA based strategy, DA-game-theory based strategy, and W/O scheduling in terms of electricity bill and PAR reduction. The proposed DA-GmEDE based strategy reduced electricity bill and PAR by 23.90% and 47.05%, as compared to W/O scheduling, respectively.

This work can be extended into various directions in future, which are described as follows:

- A system with Internet of things (IoT) can be used for energy management of the residential buildings.
- Fog and cloud concept can be used for optimal power scheduling of residential buildings instead of using a HEMC.
- An intelligent framework can be developed for residential buildings' energy optimization under renewable energy sources, electric vehicle, and utility company.
- The same framework can be extended for scalable models under advanced heuristic algorithms, analytical models, and stochastic methods.
- An innovative model can be developed for the joint consideration of residential HEMS, and real-time control of energy storage system and photovoltaic inverters to make the algorithm resilient against inaccurate prediction for both power generation and consumption.

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