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Dynamic Pricing Mechanism With the Integration of Renewable Energy Source in Smart Grid

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ABSTRACT Day-ahead electricity pricing is an important strategy for electricity providers to improve grid stability through load scheduling. In this paper, we investigate a general framework for modelling electricity retail pricing based on load demand and market price information. Without any a priori knowledge, we have considered a finite time approach with dynamic system inputs. Our objective is to minimize the average system cost and rebound peaks through energy procurement price, load scheduling and renewable energy source (RES) integration. Initially, the energy consumption cost is calculated based on market clearing price and scheduled load. Then, through reformulation and subsequent modification of optimization problem, we utilize a day-ahead price information to construct individualized price profiles for each user, respectively. To analyse the applicability of proposed pricing policy, analytical solution is obtained which is further validated through comparison with solution obtained from genetic algorithm (GA). From results, it is observed that proposed price policy is non-discriminatory in nature and each user obtained a fair electricity tariff rather than a day-ahead price, which is based on load demand and consumption variation of other users. We also show that optimization problem is sequentially solved with bounded performance guarantee and asymptotic optimality. Finally, simulations are carried in different scenarios; aggregated load and market price, and aggregated load, individualized load, market price and proposed price. Results reveal that our proposed mechanism can charge the price to each user with 23.77% decrease or 5.12% increase based on system requirements.

INDEX TERMS Demand response, optimization, non-discriminatory prices, individualized prices, smart grid, renewable energy.

NOMENCLATURE

T	total time duration
U	total number of users
ℓ	set of load
k	price factor
mr_l	must run load
d_l	discrete load
c_l	continuous load
E_{mr_l}	energy consumption of must run load
E_{d_l}	energy consumption of discrete load
E_{c_l}	energy consumption of continuous load
E_{us}	unscheduled energy consumption
E_u	total energy consumption of all users
E_{unsch}	energy consumption of unscheduled load
$\wp$	power rating
β	ON/OFF states of different loads
C	electricity cost
ψ	real time electricity price
C_{uti}^{total}	total cost of utility for selling energy
S_{pt}	electricity pricing tariff
ec_{u1}	energy consumption of user 1

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$f(t)$	function of time shift of all appliances
$\tau_{a,\ell}$	actual start time of load ℓ
$\tau_{s,\ell}$	start time of load
$\tau_{e,\ell}$	end time of load
$\tau_{sch,\ell}$	scheduled time of load
$\tau_{on,\ell}$	ON time of load
$\tau_{lot,\ell}$	duty cycle of load
Υ	peak to average ratio
φ	individualized new price signal
γ	power consumption limit
ζ	fitness of particles
η^{PV}	energy conversion efficiency (%) of PV system
E^{PV}	solar energy generated from PV system
A^{PV}	area of the solar irradiance (m^2)
$I_{(r,t)}$	solar irradiance
T_a	outdoor temperature
E_g	energy obtained form grid

I. INTRODUCTION

Electricity pricing mechanisms in a day-ahead market charge a fixed price to residential customers for specific time periods. The objective is to keep a balance between inefficient pricing system that charge a single price for a long time period and complex real time systems that prevails in electricity market [1]. The goal of dynamic pricing schemes is to make more efficient utilization of generation capacity through load scheduling, optimization and incentivising. This enables the customers to enhance their consumption level during off and on-peaks hours, without heavily relying on costlier generation and other dependences [2]–[7].

In smart grid, various types of demand response (DR) programs are available which are specifically designed to manage end user loads and CO_2 emissions reduction in response to electricity prices [8]–[13]. Generally, there are two types of DR programs being widely used while developing energy management programs; direct load control (DLC) and price based [14], [15]. In former, the utility has control to directly turn-off selected load during variation in frequency or overload conditions to maintain the power system stability [16]–[19]. Although, these schemes are useful in improving grid stability, however, this may lead to loss of social welfare and comfort of end users [20]. Thus, in the presence of dynamic load and energy consumption patterns, DLC is rather considered a passive approach in handling load. In contrast, the price based schemes [21]–[25] are specifically designed for the residential customers to actively participate in DR programs to reschedule the patterns of loads [26], [27]. In addition to price based schemes [28]–[33], others offered attractive incentives and penalties for exceeding pre-specified consumption levels. In existing researches, the electricity prices are usually given in advance, hence without optimizing price structures, the temporal complementarity among end users having different load profiles is neglected. Because, without complementarity, it seems difficult to design a flexible pricing tariffs depending on diverse power consumption and market pricing trends. Although, some researchers have done a preliminary work on pricing mechanism, however, there required more appropriate model to customize retails electricity prices in smart grid area.

In literature [33]–[42], DSM techniques are implemented in many ways focusing wholesale, distribution, and incentivized sides. In most of DSM techniques, DR programs have key importance in order to make them feasible for both utilities and consumers. Wholesale energy market focusses to keep balance between generation and demand, and transmits energy to end users on variable or flat prices depending on the nature of DR program [43]. In DLC techniques, utility has partial access to some loads on consumer sides. During high peaks, utility can shut down these loads to avoid possible blackouts. It can, therefore, improve the grid's stability, but at the cost of user comfort. Considering incentivized demand side management (DSM) techniques, a major focus is towards electricity bill reduction of end users while taking into consideration grid side [44], [45]. Authors in [46] proposed individualised demand aware price policies to calculate separate price signals for each user. Initially, a low tariff area depending on historical load demand is found, based on which the load is scheduled. Unlike other pricing schemes, this scheme charges customers depending whether the required load falls under low tariff area or not. Consequently, the load consumption cost is calculated. In [47], a customised retail price has been calculated on the basis of historical load demand data and [48] provides a uniform pricing policy based on dual tariff system. The initial problem was set to minimize the peak demand, while, the second problem is set to balance supply-demand. Another way of modelling electricity prices is the consideration of time of use (TOU) pricing tariff in conjunction with thresholding policy, which is reported in [1]. The main objective is the formulation of problem in such that adaptive prices are obtained which are load dependant. In [2], authors used a threshold policy in the sense that users can only consume power when price is below a certain threshold in order to minimize energy consumption price. However, none of the work except [1], [2], [46]–[48] considers the problem of fair pricing distribution, considering utility and user objectives. Thus, by considering the problem of unfair price distribution among all users, we have proposed a novel pricing mechanism by keeping in view the aforementioned trade-offs. The proposed work in this paper focusses both the energy retailer and consumer sides. In addition, the other constraints of grid and consumer sides are also included, while formulating the cost distribution problem. The underlying assumption is that, despite only considering the cost, comfort, or stability objectives, the affect of low, medium and high energy consumption on electricity bills are also studied. It is also worth noting here that the proposed mechanism is equally feasible for both wholesale energy retailers and incentivized consumers. Most importantly, the utility revenue remains unchanged, which is discussed in section VIII, while using the proposed individualized pricing mechanism. The key contributions of this work are given as:

- Load is categorized in such a way to facilitate all types of user including those who do not want to schedule their load in response to market clearing price. In other words, continuous power supply is provided without waiting low tariff area which can cause rebound peaks. To overcome rebound peaks problem, load of other categories is scheduled in order to balance supply-demand and cost minimization objectives.
- Based on traditional pricing mechanism (section IV-C), a novel pricing mechanism is proposed to charge customized prices to all types of users without compromising the objectives of other users.
- To compare the performance of proposed mechanism, analytical results are obtained and compared with market pricing technique (Figs. 4,5, table 3). Furthermore, the applicability of proposed pricing model is also assessed in terms of renewable energy integration. For this purpose, the user-3 is supposed to equipped a photovoltaic module and then variation on others tariff is analysed. It is found that proposed pricing model is equally feasible in case of RES integration.
- Based on the mathematical models and respective constraints on loads, the optimization problems is formulated using Knapsack techniques and a heuristic solution is obtained using GA. It is also observed that algorithm converged within feasible time to provide global optimum solution. Finally, extensive simulations are conducted to validate the proposed idea in terms of cost reduction and fair cost distribution. From results presented in table 3, it can be concluded that proposed mechanism charged electricity prices on the basis of actual consumption levels, rather than only considering electricity prices and aggregated demand.

The remaining paper is distributed in the following sections. Section II gives state of the art work, section IV discusses system model, where major attentions are given to highlight the needs and feasibility of proposed method. Section V presents problem formulation using multiple knapsack technique. Section VI then discusses the proposed load scheduling algorithms. Sections VII and VIII discuss simulation methodology and discussions, respectively. At the end, conclusion and future work have been presented in section IX.

II. LITERATURE REVIEW

Different optimization techniques [19]–[21], [49]–[54] to optimally control residential load based on market clearing prices are reported in literature. Among these techniques, [45], [55]–[60] used TOU and real time pricing (RTP), [49], [61]–[63] used proposed dynamic pricing (DP) mechanism, [46] used customized pricing (CP) mechanism, while, other pricing mechanisms are discussed in [64]–[67]. Details of each category are given as follows.

A. RTP and TOU

In [45], authors have proposed a decentralized approach to coordinate end users DR. In order to avoid chances of rebound peaks, customers' load profiles have been modified and exchanged with service provider. This process continues until service provider announces the final load profile in such that overall cost and user discomfort are minimized. It is also studied that without coordination between consumer and energy retailer, there are chances of rebound peaks which may disturb system stability. In [55], an agent based modelling and simulation technique is used to measure performance of DR in commercial building. From different perspectives, it is studied that without price based DR program, commercial buildings do not get significant impact. Furthermore, this impact differs with different scales of DR participation based on market condition. In [56], a multi-objective optimization of TOU price under multi-model structure is studied in order to reduce end user cost and satisfaction. For this purpose, load demand data is first pre-processed and then divided into different clusters using k-nearest neighbour and adaptive affinity propagation methods. To solve the optimization problem, non-dominated sorting genetic algorithm with probabilistic deviation is used to find optimal solution to achieve aforementioned objectives. In [57], particle swarm optimization algorithm is used to minimize peak-valley difference and power loss in regard with TOU pricing. To find optimal solution with reduced complexity, multi-objective constrained optimization problem is transformed into single objective unconstrained optimization problem. Results reveal that proposed strategy optimally manages the load for different time periods. It can also be seen that without TOU pricing, the load faces more fluctuations. While, the load profile seems more stable when employ constrained and unconstrained methods. However, this work is different from our proposed work in such a way that real time load patterns and price are not considered, which may discourage users to participate in DR programs. In [58], a heuristic DR scheme is used to model end user appliances without taking individualised consumption patterns. In order to develop optimized consumption pattern, a load demand vector is obtained from energy management controller using stochastic programming with the objective to PAR minimization.

B. DP and CP

The work reported in [49] has considered a DP scheme with the objective of energy efficiency in SG. With consideration of renewable energy buying-back scheme, a DP scheme is reformulated as a convex optimization dual problem, based on which a time dependant price is developed. As the scheme works in a distributed fashion, so both the utility and end user take their benefits. Unlike other schemes, the objective of this work is novel, however, end users having cost reduction as a primary objective are not given priority. In [61], a Stackelberg game approach is developed to model interaction between user and electricity producer to find possible trade-off between a consumer surplus and net-profit. Furthermore, a renewable energy storage system is also integrated to analyse the behaviour, that shows that benefits go to retailer if the installed capacity is smaller. On the other hand, the user can take benefits of renewable energy if capacity increased from a given threshold level. Authors overcome this problem by using Reinforcement learning strategy without any priori knowledge of both, consumers and retailer sides. In [62], a service provider acts as a broker between utility and customer to purchase electricity from utility company and selling back to end users. The inherent uncertainties due to dynamic load consumption and aggregator based price signal, a reinforcement learning scheme without a priori knowledge is used that allows each of the service provider to learn its strategy. DP [62], however, is useful for utilities in stabilizing the electric grid. On the other hand, it is difficult to implement due to lack of knowledge of variation in consumer load demand. Similarly, consumers also face difficulties in managing their loads due to price variation. The work [63] uses a TOU mechanism to develop a DP based on customers load profiles. The load demand data is communicated to system operator. In a response, a daily price signal comprising low, mid and high pricing tariffs are designed to reduce high peaks. In [46], a demand aware price policy has been developed based on individualized load demand profiles of all users. Unlike other schemes, this scheme differs in such a way that each user receives a separate price signal which is discriminatory in nature. It means, the end users are provided the facility to manage their load demand without heavily relying on market price signal only.

C. OTHER SCHEMES

The work presented in [64] is based on a three stage framework, where DR aggregator determines the incentives offered to participating customers for joining load management programs. Initially, the aggregator interacts with wholesale electricity retailer and end users to model their behaviours using satisfying theory. Then based on aspiration level and disutility, aggregator decides the tariff and incentives. Another work presented in [65] used a simplified conduction heat transfer method to model energy consumption in a residential unit. In [66], authors used a model predictive control theory to reduce energy cost through incorporating building dynamics. Is is observed that, rather than saving energy from building material, up to 15% & 28% energy can be saved depending on other factors such as outside temperature and efficient load scheduling. A non-cooperative game approach is developed considering customer's behaviours to decide whether or not it is feasible for a customer to participate in load management programs [67]. Because, in traditional load management programs, it was pre-assumed that customers are rational in their decisions and voluntarily participate in load management programs. In order to reduce electricity cost, a prospect theory (PT) is used to explicitly incorporate the impact of user behaviour on DSM decision. Furthermore, a new algorithm based on fictitious game is used to develop a Nash equilibrium.

Detailed literature review shows that few researches proposed a day-ahead pricing based optimal load scheduling to minimize electricity consumption cost [44], [45], [55]–[58], while other works are based on DP and customized pricing mechanisms [61]–[63]. Among price based DR mechanism, few authors proposed customized pricing mechanisms, which are developed based on day-ahead pricing schemes [46], [64]–[67]. The works discussed in [45], [55], [56] use price based DR mechanism to reduce cost and rebound peaks. However, the authors do not consider fair distribution of electricity price among all users. Similarly, the main focus of [57] is to minimize power loss minimization. Unlike our proposed work, the focus of [58] is to schedule appliances on the basis of aggregated load profiles leading to unfair price distribution. The authors in [46] have done a remarkable work by considering individualized load demand profiles. In conclusion, the focus of other works is to schedule end user load based on market or customized price signal in such a way to minimize cost, rebound peaks and system stability. However, to facilitate end users in terms of fair pricing through individualized load consumption and pricing policies is still missing and an needs to be considered carefully.

III. MOTIVATION

As discussed in section II, the DSM techniques are efficient in reducing energy consumption in response to dynamic price signals which are often been recognized to reduce high peaks [11], [12]. In these works, end users can change their consumption schedules in response to price signals rather than static energy optimization techniques [13]. It increases the stability, flexibility [28], [29] and reliability [30], [31] of electric grid by managing end user's loads. DSM is used for its ability to increase the stability of electric grid with reduced cost [32], [33]. Furthermore, by encouraging end users to participate in DSM programs in response to dynamic price signals, the need for more expensive electricity generators to meet peak demands can be minimized. DSM programs are also useful in balancing the energy demand and generation capacities. Otherwise, these generating facilities would have been idle during off-peak hours which may lead to reduced revenue. By introducing DSM programs, participating, and electricity suppliers all can take benefits. The deregulations of the electricity pricing markets, and advancements in ICT [32], [44], have motivated for the development of more optimal DSM programs. As a result, energy retailers, and electricity transmission organizations have been implementing DSM programs to facilitate end users with lower prices, and increase the elasticity from generation facilities to retail markets [34]. In this way, end users can reduce their electricity bills alongwith maximum comfort. DSM researchers have addressed the: (i) minimization of energy consumption and user discomfort, (ii) the stabilization of energy generation and electricity prices, using optimization techniques [35], [36], [44]. Moreover, they also considered the integration of RESs, such as solar, electric vehicle, energy storage systems, etc., [37]–[39], centralized and decentralized load management techniques [44], models of consumer behaviours [40], and the trends of DSM participation [41].

Despite the importance and benefits of DSM programs, utilities and researchers have reported different approaches on their objectives. A common approach being adopted by DSM researcher is to maximize the end user comfort in terms of electricity cost minimization in response to time varying price signals. Meanwhile, DSM researchers focussing utility side have introduced baseline capacity limits to enhance the stability of power grid during peak hours [42]. Furthermore, they also introduced the peak power plants to compensate the load while charging high prices during particular hours [33]. From the above discussion, we can easily conclude that the major objective of DSM and DR techniques is twofold: (i) to minimize the electricity cost of end users alongwith high comfort level, and (ii) minimize the high peaks alongwith electricity cost reduction [68], [69]. Here is a trade-off between user comfort and electricity cost reduction. If the focus is towards electricity cost minimization, it is very difficult to achieve high comfort at the same time. However, some techniques are being proposed which take into account this trade-off and proposed different solutions. But, no one considered the DSM by taking into account individualized energy consumption patterns regardless of DR signal which is based on aggregated energy demand.

This work builds upon the same concept which is given in [54], in which the analytical simulations were performed to highlight the impact of individualized price profiles on end user cost. In the proposed work, we first develop a mathematical model for obtaining price profiles of all users. Then the well established optimization problem is solved by using non-linear programming (NLP) technique to schedule connected loads using market clearing price. Here, it is important to understand that the load scheduling is performed on the basis of dynamic electricity prices. Furthermore, the proposed work is not primarily designed to control or design new electricity prices. Thus, the mathematical model presented through Eqs. 1-8, however, does not address the individualized energy consumption trends creating discrimination in electricity prices. So, to overcome this limitation, the mathematical model is further modified to consider both, individualized load trends and dynamic prices. Eventually, along with fair price distribution among all users, a balanced load profile is also obtained which ultimately improves power system stability. In addition, on-site RES is also incorporated to further visualize the impact of proposed mechanism on end user cost profile. However, prior to this, loads are categorized on the basis of power rating and user preferences. Finally, the results obtained using traditional and proposed mechanism are compared to validate the key findings (Table 2).

The optimization and scheduling of residential loads are of greatest interest in the world due to variations in energy demand. As the natural energy sources are depleting quickly, and the world is struggling in finding green energy sources to fulfil future energy demand with reduced carbon emissions. Furthermore, the additional reliance on green energy and climate control buildings exacerbates reliable delivery of power with forecasted demands to ensure reliability. Fortunately, the potential customers use global pricing schemes (i.e., RTP, TOU) within a single utility or DSO. So that end user and utility can take equal benefits with mutual information sharing via AMI. Although DR programs are utility centric where end users take monetary benefits, encouraging by utilities to take part in these programs. As discussed in section III, DR prices are calculated on the basis of aggregated energy consumption. In response, the low or medium energy users can not take monetary benefits according to what have they contributed in DR. So, keeping in view the aforementioned limitation, the proposed work directly addresses the cost minimization problem to benefits potential users. In this regards, this work has direct applicability to the regions where smart grid infrastructure is being implemented (i.e., NYISO, PJM, [43], [70]).

IV. SYSTEM MODEL

We consider a smart grid model in which the energy from power grid is distributed among several units/homes to fulfil load demand. Each home is equipped with different type of loads and a smart meter to communicate with the energy management controller (EMC) to collect energy consumption information of all users. In addition, $U3$ is equipped with a RES to further analyze the impact of RES on the price calculation of other users. The rest of the units are assumed to get energy from main grid. In day-ahead DR programs, generally the aggregator is responsible for the calculation of electricity price signals which are transmitted to consumers using AMI [17]. Then utility sets the electricity price on the basis of total load demand received from smart meter. Regarding EMC, it can be considered as a standalone entity or embedded in retailer/aggregator side, where individualized electricity prices are calculated on the basis of load demands. Then these prices are transmitted to the respective units via smart meters. In order to best describe the proposed mechanism, we first categorized the loads in each unit. The Fig. 1 gives the conceptual diagram of the proposed model.

A. LOAD TYPES

Based on energy demand and power rating, the loads are categorized into the following categories: (i) discrete load (d_l), (ii) continuous load (c_l), and (iii) must run load (mr_l), (table 1), such that $[\ell \in d_l, c_l, mr_l]$. The EMC is responsible to control the working cycles of d_l and c_l, respectively. While the mr_l does not take part in scheduling process, so as to increase the user comfort. Because, these loads are considered to be turned ON whenever users require. The duty cycles of d_l can be altered during operation time due to their flexible nature. In other words, users can bear delay due to variations in appliance starting time. Whereas, c_l cannot be turned OFF

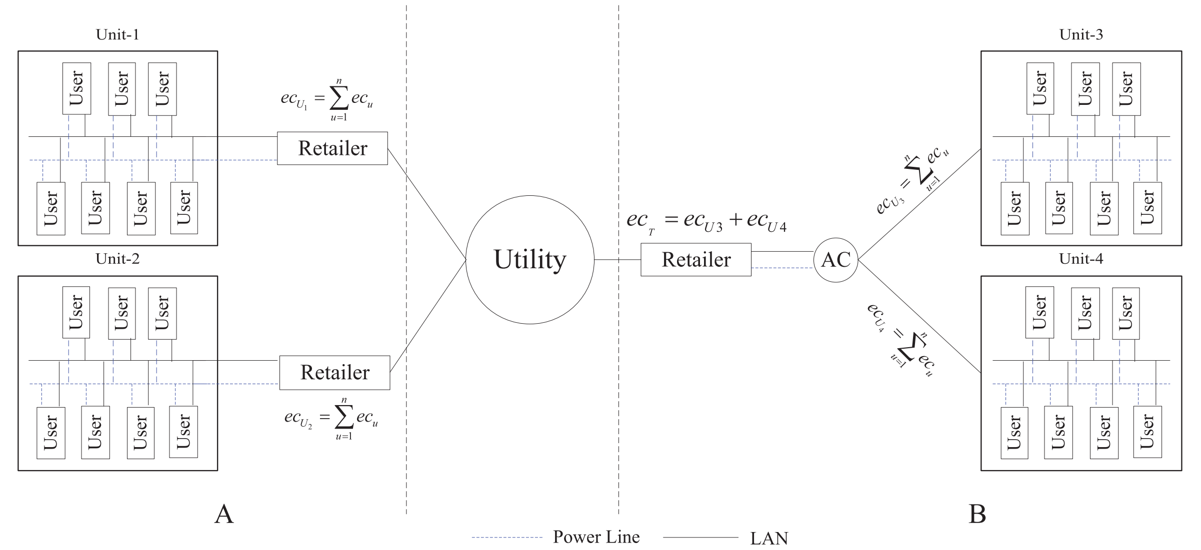

FIGURE 1. Conceptual diagram for energy cost calculation: (A) traditional scheme, (B) proposed scheme.

TABLE 1. Appliance energy consumption and duty cycle requirements.

Load Type	Loads	Duty cycle (Hour)	Energy consumption (kW)
mr_l	Load 1	20	2.5
	Load 2	24	3
d_l	Load 3	5	2
	Load 4	7	2.5
c_l	Load 5	8	3.5
	Load 6	8	3

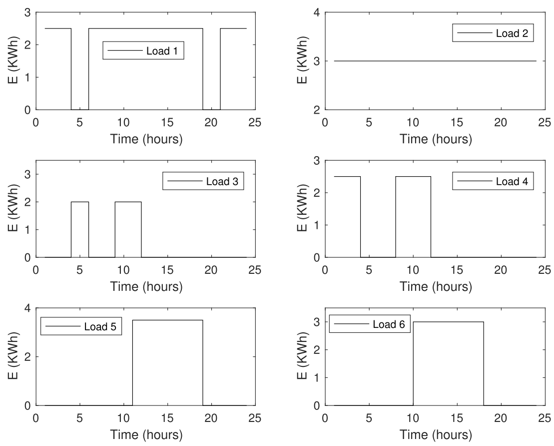

FIGURE 2. Energy demand profile over 24 h period.

during operation time. Because, these loads complete their duty cycles once they are turned ON. The load demand of each load is shown in Fig. 2. While the detailed working of these loads are discussed below.

1) MR_L

We assume that mr_l does not take part in DR program, hence it is not scheduled over the given time. Although, this load has specified scheduling intervals, which is 24 hours, as shown in Fig. 2, load 2. So, it is observed that this load needs continuous supply of power in order to fulfil the required task during given time interval. The energy demand and power rating of mr_l can be denoted by E_{mr_l} and $\wp_{mr}$, respectively. The total energy consumption of mr_l is calculated by using the following equation:

$$E_{mr_l}(t) = \sum_{mr_l} \sum_{t \in T} \Big(\wp_{mr_l}(t) \times \beta_{mr_l}(t) \Big), \tag{1}$$

where, β_{mr_l} denotes the ON/OFF state of mr_l in the given time slot t.

$$\beta_{mr_l}(t) = \begin{cases} 1 & \textit{If load is ON} \\ 0 & \textit{If load is OFF}. \end{cases} \tag{2}$$

2) D_L

We assume that power demand of d_l can be scheduled from given time slots to any other time slots such as to reduce overall cost. In other words, this load has deferrable nature and its normal working can be shifted or changed regardless to user specified time intervals. This ensures minimum power consumption cost, however, user comfort in terms of scheduling delay has to be compromised. The power consumption of d_l is represented by E_{d_l}. Let, $\wp_{d_l}$ denotes power rating of d_l, then total power demand is calculated as:

$$E_{d_l}(t) = \sum_{d_l} \sum_{t \in T} \Big(\wp_{d_l}(t) \times \beta_{d_l}(t) \Big), \tag{3}$$

where, β_{d_l} is the state of d_l in a particular time slot t and is given as follows:

$$\beta_{d_l}(t) = \begin{cases} 1 & \textit{If load is ON} \\ 0 & \textit{If load is OFF} \end{cases} \tag{4}$$

3) C_L

We assume that, unlike d_l, the power demand of c_l can be scheduled, however, the normal working can not be interrupted once scheduled. For example, if a load has 5kW power demand, then scheduling algorithm fulfils the required demand by rescheduling the load in different time slots, based on minimum priced intervals (Fig. 2, loads 3&4). However, the customers have to bear more scheduling delay. Eventually, this load would contribute in achieving better optimized results, as compared to other types of load. Because, their normal working can not be disturbed once they turned ON, i.e., they must complete their scheduled duty cycles. The total energy consumption and power rating of c_l are denoted by E_{c_l} and $\wp_{c_l}$, respectively. The total energy consumption of c_l is calculated by using following equation:

$$E_{c_l}(t) = \sum_{c_l} \sum_{t \in T} \Big(\wp_{c_l}(t) \times \beta_{c_l}(t) \Big), \tag{5}$$

where, β_{c_l} denotes the state of c_l and can be written as follows:

$$\beta_{c_l}(t) = \begin{cases} 1 & \textit{If load is ON} \\ 0 & \textit{If load is OFF}. \end{cases} \tag{6}$$

The total energy consumption $E_u(t)$ of all users is equal to the sum of aggregated energy consumption of individualized users which is given as:

$$E_u(t) = \sum_{u \in U} \sum_{t \in T} \Big(E_{mr_l,u}(t) + E_{d_l,u}(t) + E_{c_l,u}(t) \Big), \tag{7}$$

B. ELECTRICITY PRICE MODEL

This section provides brief information about the day-ahead electricity market. As it is understood that electricity price signal is dynamic in nature, due to variations in end user energy demand. Consequently, it is very difficult rather impractical for regulatory authorities to fix the electricity prices for certain time period. So, it can be expected that electricity price signal varies as demand varies. However, in day-ahead market, the price can be fixed for certain interval of time if the load remains within acceptable limits. But, irrespective of all the information, there is a probability that loads can be varied which can eventually disturb the stability of power grid. To avoid all these problems and risks, the flexible DR programs are being widely used by encouraging the consumers to take part in these programme. Users can take part in DR programs by modifying their energy consumption schedules in regards to the day-ahead price signal. This mechanism also allows the end users to increase or decrease their energy consumption in different time slots. In this way, users can get monetary benefits and utilities avoid the risk of grid instability during high peak hours. This approach, however, is quite efficient and being widely used now a days. But there are certain problems associated with these types of techniques. For example, if electricity pricing signal is totally based on aggregate energy consumption, then it might not be feasible for all types of consumers. Because, low, medium and high energy consumers are getting the same prices, irrespective to their individualized energy consumption patterns. Moreover, utilities are getting the bill in response to what they are selling. But, the low and medium energy consumers affects due to this strategy. This is the underlying problem in DR programs focussing user benefits which is highlighted and solved in this research work. In the following sections, the traditional method used to calculate energy cost is given. Then based on this, the individualized prices in response to energy demand of associated users are calculated (Fig. 3).

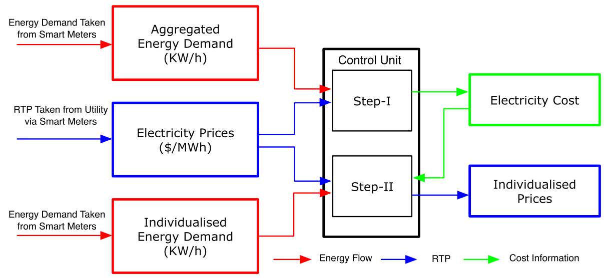

FIGURE 3. A conceptual diagram of proposed system model for the calculation of individualized price profiles.

C. TRADITIONAL METHOD

In recent DR programs, used in wholesale electricity market, day-ahead electricity prices (hourly prices) are calculated on the basis of aggregated energy consumption of any specific region. Whereas the electricity unit price for next hour depends on the current energy consumption level, which can be calculated using the following expression:

$$C_u(t) = \sum_{u \in U} \sum_{t \in T} \Big(E_u(t) \times \psi(t) \Big) \equiv C_{uti}^{total} \tag{8}$$

Eq. (8) shows that the energy consumption cost of $[u \in U]$ must be equal to utility revenue calculated on the basis of load consumed. In case of TOU or day-ahead RTP, the $\psi(t)$ is assumed to be fixed for the time duration t. This expression Eq. 8 is generic and used for electricity cost calculation. However, the drawback associated with this method is that the energy prices set by utilities apply to any specific region are not based on individualized energy consumption patterns. But these are rather on the basis of aggregate energy consumption of that particular region [6]–[10], [61]. Due to this strategy, the low, medium and high energy consumers are charged equally which penalizes the low and medium energy users. To overcome this problem, there must be a mechanism which charged electricity prices to the associated consumers on the basis of their consumption level rather than on aggregate basis. To further highlight the problem and its effect on electricity bill, the section VIII provides the details.

D. PROPOSED METHOD

The details given in section IV-C reveal the possible drawbacks and limitations regarding electricity cost saving perspective. It is also discussed that aggregated price policies are feasible for market retailers, reducing user benefits.

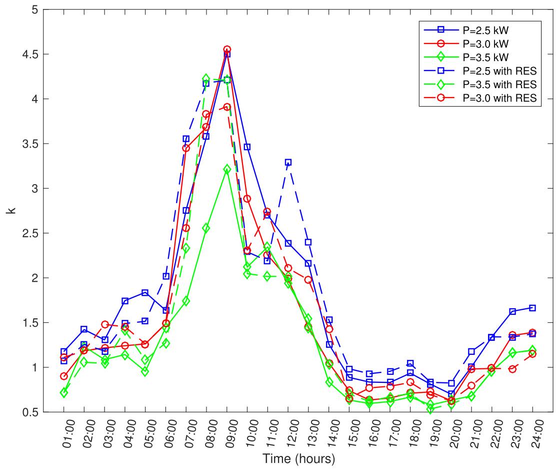

FIGURE 4. The dynamic variation in the values of k against different load and RES integrated load profiles, Eq. (9).

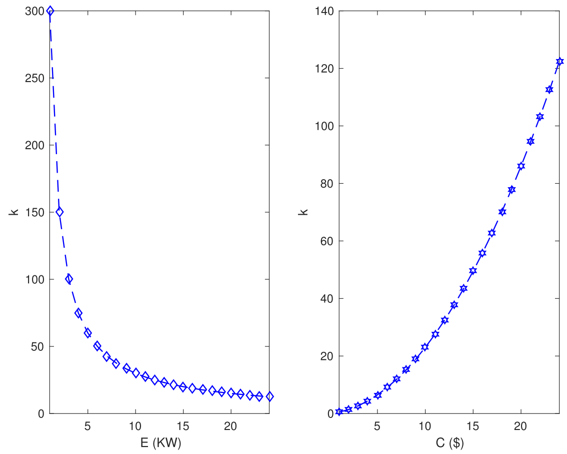

FIGURE 5. The behaviour of k as a function of E and C.

To overcome such types of problems, we have proposed a novel mechanism to calculate electricity sub-prices in accordance to: (i) the individualized energy consumption patterns, and (ii) aggregated electricity price signal. Because, it is very difficult for utility to design/calculate a separate electricity price signal for each user. Consequently, it can further increase the communication overhead based on which the DR programs work. In order to calculate individualized prices for potential users, we develop a mathematical expression which calculates these prices for each user/unit according to their consumption levels. For this purpose, we need; a day-ahead electricity price signal obtained from retailer/utility, and individualized energy consumption of U obtained from smart meters. Then based on these parameters, the price factor k for each user/unit is calculated by using the following equation:

$$k_u(t) = \frac{\sum_{t\in T}\sum_{u\in U}(E_u(t) \times \psi(t)}{\sum_{t\in T}\sum_{u\in U}(E_u(t))^2}. \tag{9}$$

In Eq. (8), $C_u(t)$ denotes the total energy consumption cost of n users in response to day-ahead electricity price signal ψ. In contrast, Eq. (9) shows that k depends on the energy consumption of each unit. In other words, if any unit consumes more energy, then the values of k will be higher and vice versa. The value of k in accordance with the load profiles of individualized users is shown in Fig. 4. While the behaviour of k with respect to electricity cost and energy consumption is shown in Fig. 5. The figure also shows the variation in k when RES is utilized. The variations in value of k shows the individualized energy consumption trends and its possible impact on electricity price signal (Fig. 11). Because the proposed mechanism has the objective to distribute the electricity prices in accordance with per slot energy consumption of the users, while preserving the retailers objective.

1) NON-DISCRIMINATORY PRICES

Intuitively, in order to have consumers agreeing on paying electricity bills on the basis of individualized prices, it is mandatory that these prices must be non-discriminatory. These are also important for retailers and/or DSO, as discriminatory prices may reduce the potential users accepting these prices. In the proposed work, the individualized prices calculated on the basis of load profiles are non-discriminatory. Where, the individualized prices depend on the respective load profiles as discussed in section IV-D. In contrast, the traditional method (section IV-C) uses market based prices irrespective of individualized load profiles. We define a pricing tariff $S_{pt} = (ec_{u1}, ec_{u2}, ec_{u3}, \psi_u, k)$, the individualized prices $\varphi(t)$ on the basis of k, for each user:

$$\begin{bmatrix} \varphi_{u_1}^{t_1} \\ \varphi_{u_2}^{t_2} \\ \varphi_{u_3}^{t_3} \\ \vdots \\ \varphi_U^T \end{bmatrix} = \begin{bmatrix} k_1^{t_1} \\ k_2^{t_2} \\ k_{3^{t_3}} \\ \vdots \\ k_U^T \end{bmatrix} \times \begin{bmatrix} E_{u_1}^{t_1} & E_{u_1}^{t_2} & E_{u_1}^{t_3} & \cdots & E_{u_1}^T \\ E_{u_2}^{t_1} & E_{u_2}^{t_2} & E_{u_2}^{t_3} & \cdots & E_{u_2}^T \\ E_{u_3}^{t_1} & E_{u_3}^{t_2} & E_{u_3}^{t_3} & \cdots & E_{u_3}^T \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ E_U^{t_1} & E_U^{t_2} & E_U^{t_3} & \cdots & E_U^T \end{bmatrix} \tag{10}$$

where, $\varphi_1(t), \varphi_2(t), \varphi_U(t)$ are respective prices for buying electricity form retailers. The total electricity cost C_u of U users is calculated as follows:

$$C_U(t) = \sum_{t\in T}\sum_{u\in U}\Big(E_u(t) \times \varphi_u(t)\Big). \tag{11}$$

The steps involved to calculate individualized DR signals for user U are given as:

1) a set of u users $u \in U$ directly connected to retailers via AMI. In traditional DR program, u (i.e., unit-1 and unit-2 in Fig. 1) are directly connected to retailers. While in the proposed method, u (i.e., unit-3 and unit-4) are connected to the AC entity which is responsible for the calculation of DR signals for individual users. Then the aggregated cost on the basis of net load is sent to utility vis retailer. Here, the accumulator AC (Fig. 1, i.e., centralized EMC) is considered as a separate entity. However, it can also be embedded in retailer unit.
2) a time slot $t \in T$, typically with a horizon of 24 equal length time slots.

3) the desired energy demand profile (kW) of u obtained from AC.
4) the per-unit electricity tariff ψ_t (i.e., TOU, RTP) coming from electricity retailers.
5) then on the basis of ψ_t and load profiles of u (these profiles may be computed on the basis of historical data of $[u \in U]$ in T), AC calculates the DR signals in regards to individualized energy consumption profiles.
6) then consumers reschedule their loads on the basis of updated DR signals. Please note that maximum energy consumption limit is also implemented in optimization algorithm to reduce the chances of high peaks on grid side. Otherwise, the grid stability could be affected.
7) in each time slot $[t \in T]$, AC updates the price signal for each u on the basis of individualized load profiles.

2) DISCUSSION ABOUT K

As discussed in section IV-D, the proposed scheduling mechanism for residential DR depends on factor k (Eq. 9). Where, the k further depends on two factors; E_u and ψ. We provide numerical results (Fig. 4 to show the dependence of E_u and ψ on k, which is a key factor for the calculation of individualized prices. The left side of Fig. 5 shows the relationship between energy consumption and k, while the Fig. 4 shows the variation in k using: (i) energy demand pattern without RES, and (ii) energy demand pattern with RES. The considered load and respective categories have been given in table 1. Fig. 4 shows that when energy consumption increases, the value of k decreases. Because, the energy consumption factor E_u^2 is in denumerator in Eq. (9). In contrast, the right side of Fig. 5 shows the relationship between C and k. It is clear from the figure that cost increases as we increase the value of k, which depends on E. In conclusion, it is obvious from Fig. 5 that individualized prices depend on k which is the base of proposed work.

E. USER COMFORT

From detailed literature review [21]–[23], [25]–[37], it can be concluded that most of the energy management schemes have cost reduction as a major objective. Whereas, other schemes have considered both the cost reduction and comfort maximization as primary objectives [4], [5], [44]. Although, cost reduction objective satisfies the end-users which can bear extra delay due to load scheduling process. In contrast, comfort maximization may reduce electricity cost and vice versa. According to the literature, user comfort can be defined as follows [44], [76]:

$$f(t) = \sum_{t \in T} \sum_{u \in U} (\tau_n(t)), \tag{12}$$

where, $f(t)$ is function of time shift of all scheduled loads under user preferences and lifestyle constraints. In Eq. (12), the variable τ_n is equal to $|s_n - \alpha_n|$, defines the time shift of appliance n. In other words, the discomfort level is equal to the total number of hours shifted from specified time slot.

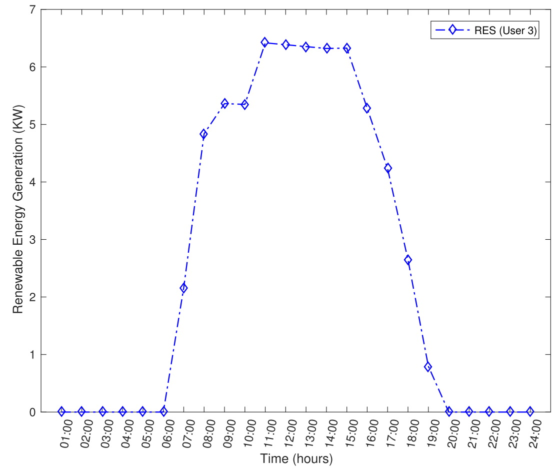

FIGURE 6. Renewable energy profile over the period of 24 h used in U-3.

So, the objective function is to reduce this time in order to provide maximum comfort alongwith minimum cost. Here, one important point is that user comfort maximization and electricity cost reduction are contradictory objectives and difficult to achieve [44].

F. RENEWABLE ENERGY INTEGRATION

To further analyze the performance of proposed mechanism, we assume that $U3$ is equipped with photovoltaic RES. The proposed mechanism utilizes the renewable energy as a primary source to reduce the electricity prices (i.e., individualized prices). The remaining units use the utility energy as a primary source and receive the prices on the basis of energy consumption. The solar PV energy used in the proposed work is obtained from the model demonstrated in [71], [72], Eq. 13. The output power is shown in Fig. 6:

$$E^{PV} = \eta^{PV} \times A^{PV} \times I_r(1 - 0.005(T^a - 25)). \tag{13}$$

Keeping in view the aforementioned points, the proposed work not only considers the delay based comfort, but also provides end user comfort with extra cost savings to low and middle class users. For this purpose, sections IV-A and IV-B discus different types of loads alongwith preferences and energy price model used in the proposed work, respectively. Then, section VIII discusses the real time benefits in terms of cost reduction and comfort maximization.

V. PROBLEM FORMULATION

In this work, multiple knapsack (MK) problem formulation technique has been used to formulate load scheduling problem [77]. In general, knapsack is a formulation technique in which the "knapsack" is filled with multiple "objects" considering its "values" to take maximum benefits. The MK technique has been used to formulate the proposed load scheduling problem using individualized pricing. However, prior to the formulation, following assumption are considered:

1) Multiple time slots t are considered as a "MK".
2) Number of loads have been considered as "objects".
3) Energy consumed by each user is taken as "weight".
4) Energy consumption cost of each user is considered as "value".
5) Energy consumption limit in each time slot t is considered as "capacity".

By taking into consideration the aforementioned assumptions, we formulate the objective function with the aim at reducing electricity cost in association with different constraints. On the other hand, for reliable and un-interruptible energy supply, the power grid must not overburdened due to heavy load. To achieve this objective, a limit on total energy consumption in each time slot t and RES are also considered. So the total power consumption of each user does not exceed the maximum power capacity in each t. This mechanism is being widely used in different DSM programs [4], [5] and has provided efficient results. Although, it increases the stability of power grid, however, it can disturb end user comfort to some extent. But, the major focus of this work is towards facilitating end users with significant amount of bill reductions.

The objective function is divided into two parts:

1) in the first part, the load scheduling problem is formulated and cost reduction objective is achieved by using day-ahead pricing signal.
2) in second part, the load scheduling problem is formulated and cost reduction objective is achieved using individualized prices.

A. DISTRIBUTED ENERGY MANAGEMENT PROBLEM FORMULATION

In distributed energy management mechanism, the load has been controlled on the basis of RTP signal obtained from utility as shown in Fig. 7. In first phase, energy consumption limit is not imposed, because the EMC works in a distributed way and is independent to the other units. The optimization problem is then formulated as follows:

$$min \sum_{t\in T}\sum_{u\in U}\Big(E_u(t)\times\psi_u(t)\Big) \tag{14}$$

$$s.t : \tau_{s,\ell} \leq \tau_{a,\ell} \leq \tau_{e,\ell}, \tag{14a}$$

$$\tau_{sch,\ell} = \tau_{on,\ell}, \quad \forall\, mr_l, \tag{14b}$$

$$\tau_{sch,\ell} = \tau_{on,\ell} \leq \tau_{e,\ell} - \tau_{lot,\ell}, \quad \forall\, de_l, \tag{14c}$$

$$\tau_{sch,\ell} = \tau_{on,\ell} \leq \tau_{sch,\ell} \leq \tau_{on,\ell}+\tau_{lot,\ell}, \quad \forall\, ce_l, \tag{14d}$$

$$\beta(t) = \tau_{lot}. \tag{14e}$$

where, Eq. (14) is cost minimization objective function, Eq. (14a) denotes upper and lower limits on load start and end times, Eqs. (14b, 14c, 14d) give scheduling horizons for mr_l, de_l and ce_l, respectively. Eq. (14e) demonstrates that total working hours of any load, that must be equal to its duty cycles.

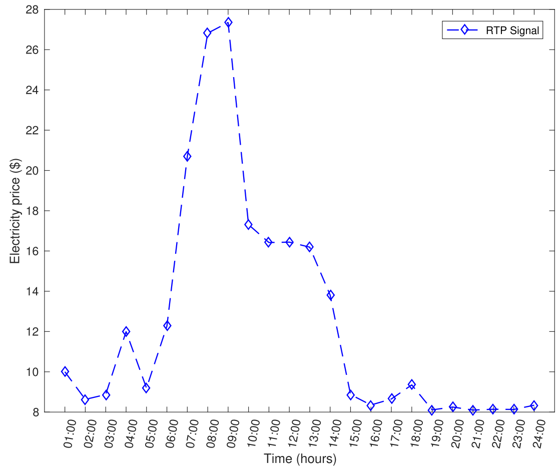

FIGURE 7. RTP signal used in the proposed work which is obtained from day-ahead electricity market [43].

B. CENTRALIZED ENERGY MANAGEMENT PROBLEM FORMULATION

In this mechanism, all users share their energy consumption profiles in neighbourhood area network. In first step, the electricity cost in t is calculated using electricity prices ψ obtained directly form utility. In second step, the energy consumption of each user and their respective cost have been calculated. In third step, the individualized electricity prices on the basis of energy consumption data in previous hours are calculated as shown in Fig. 11. It is worth noting here that for the calculation of individualized prices φ, electricity price signal obtained form utility and energy demand patterns are used as input parameters. In response, φ for each unit u are calculated. In this way, electricity prices are fairly distributed among all units while preserving utility revenue. Furthermore, the total energy consumption limit is imposed in optimization problem to lower high peaks on grid side. The centralized problem is now formulated as multiobjective optimization as written below:

$$min \sum_{t\in T}\sum_{u\in U}\Big([E_u(t)\times\varphi_u(t) - E^{PV}(t)] + f(t)\Big) \tag{15}$$

$$s.t : \beta(t) = \tau_{lot,\ell}, \tag{15a}$$

$$\sum_{u\in U}\sum_{t\in T}\Big((E_u(t)\times\beta(t))\leq\gamma_u(t)\Big), \quad \forall, [\ell \in mr, ce, de] \tag{15b}$$

$$\sum_{u\in U}\sum_{t\in T}\Big(C_u(t) - U^{total}_{uti}(t)\Big) = 0. \tag{15c}$$

$$\sum_{u\in U}\sum_{t\in T}\Big(E_{u3}(t) = E_g(t)+E^{PV}(t)\Big) \quad \forall[\ell \in mr, ce, de]. \tag{15d}$$

where, Eq. (15) is cost minimization objective function, Eq. (15a) shows that operating hours of any load must satisfy its duty cycle requirements, Eq. (15b) denotes maximum energy consumption limit considered to minimize high peak during overload conditions. Eq. (14c) provides the cost balance expression (i.e., utility revenue must be equal to total power dispatch). The Eq. (15d) shows that ($U3$) utilizes RES as a primary energy source along with grid energy. While the rest of the users fulfil their energy demand from electric grid only. Initially, the energy consumption limit can be calculated using the expression:

$$\gamma^1(t) = max\left(\sum_{t\in T}(\beta(t) \times E_{us}(t))\right). \tag{16}$$

For u, the above equation would become:

$$\gamma_u(t) = \gamma^1(t) - \sum_{t\in T} \beta(t) \times E_u(t). \tag{17}$$

where, Eq. 17 gives power consumption capacity limit for u, which depends on Eq. 16.

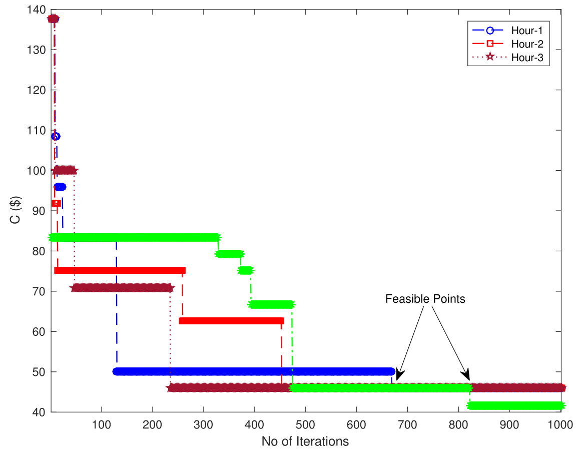

FIGURE 8. Behaviour of GA w.r.t., cost and total number of iterations in achieving global optimal solution.

VI. PROPOSED ALGORITHMS

The DR strategy is applied to both distributed and centralized schemes. For each unit, there is a distributed EMC to control load in response to the traditional RTP. On the other hand the AC (Fig. 1) calculates ψ on the basis of aggregate energy consumption of each user $u \in U$, which results in final energy consumption pattern of the user. Each user is equipped with several types of loads with different control parameters. To deal with all these parameters, i.e., duty cycle, energy consumption, priorities of interruption according to load type, is a challenging task. The evolutionary algorithm such as genetic algorithm (GA) [36], [73]–[75] has the ability to solve load scheduling problem in association with all constraints. GA has good computational ability and high convergence rate as compared to other mathematical approaches [62]. Because, to find global optimum solution in the search space when many local optimum solutions are present is a classical problem. In this regard, the GA has the ability to find global optimum with high accuracy through parallelizable search. It is evident from the Fig. 8 that proposed algorithm is designed in such a way that it always converged within certain bounds and limits. For example, in each time slot, the algorithm searches global optimum solution from the entire search space, where other local optimum solutions exist. In order to avoid GA being trapped in a local optimum solution, we have expanded the search space (i.e., 400 population size). It is then ensured that the optimal solution is always feasible. Because, if we consider $\min_{\mathbf{z}\in\mathbf{S}} f(\mathbf{z})$ as a standard minimization problem, where, $\mathbf{S} \subset I\!R$ denotes the feasible set. Any $\mathbf{z} \in \mathbf{S}$ is considered to be feasible point and conversely, any $\mathbf{z} \in I\!R \setminus \mathbf{S} := \{\mathbf{z} \in I\!R : \mathbf{z} \notin \mathbf{S}\}$ is infeasible. In another sense, a solution $\min_{\mathbf{z}^1\in\mathbf{S}} f(\mathbf{z})$ is known as Pareto optimal solution if and only if there does not exist another solution in the same search space which dominates it. In our case, all solutions are Pareto optimal (Fig. 8).

A. DISTRIBUTED ALGORITHM FOR EMC

In a distributed manner, we assume a user $u \in U$ has a variety of loads with different parameters. The EMC communicates with different types of loads, and take energy consumption, duty cycle and priorities of interruption as input parameters the algorithm. After that, the EMC performs scheduling for respective user in order to reduce electricity bill. In EMC the traditional price signal is used, in which each user has equal price independent to their energy consumption.

The working steps of proposed distributed EMC algorithm are given as follows (algorithm 1):

B. CENTRALIZED ALGORITHM FOR C-EMC

In a centralized manner, the EMC manages the load on the basis of energy consumption patterns and assigns different prices for each user $u \in U$. The EMC communicates with utility and local EMC to achieve cost minimization and PAR reduction goals. For this purpose, each user shares its scheduled energy consumption pattern provided by the distributed EMC to AC. Then on the basis of these patterns, AC assigns different prices to each user. Here, it is assumed that the price is distributed among all users in such a way that the aggregate energy consumption cost of all users is same as in the case of distributed DSM strategy discussed earlier. In contrast, the individual energy consumption cost may differ in this case, and is depends on their energy consumption. High energy consumers always pay their bills according to the load consumed and vice versa. The factor by which the price among the users' is distributed is calculated by using Eq. (9). This mechanism assures grid stability in terms of reduced peaks by restricting consumers to limit their consumption. The working steps of proposed centralized EMC algorithm are given as follows (algorithm 2):

VII. SIMULATION METHODOLOGY

The optimization models discussed in the section IV-D are tested and evaluated on a hypothetical test case where different homes/units are considered. It is assumed that each home has different types of loads having different duty cycles, and power ratings as given in (table 1). To further check the validity of the proposed mechanism, $U3$ is equipped with

Algorithm 1 Distributed EMC Algorithm

Required Unscheduled pattern, population size, max. generations, N, ψ.
Initialize random population which represents the patterns of appliances.
for t = 1:24 **do**
EMC checks for available RES source of user 3.
  if $g(t) \geq es_{u3}(t)$ **then**
Turn ON the appliance i of user 3.
  else
    for i = 1:popsize **do**
Evaluate fitness function eq. (14)
$\zeta = fitness$
      if $(\zeta(i) < \zeta(i-1))$ **then**
        $\zeta(i) = \zeta(i)$
        if $ce_i(t-1) == 1$ **then**
          if $(\tau_i \leq \tau_{lot})$ **then**
            $c(t) = 1$
          end if
        end if
        if $de_i(t) == 1$ **then**
          if $(\tau_i \leq \tau_{lot})$ **then**
            $de(t) = 1$
          end if
        end if
      else
        $\zeta(i) = \zeta(i-1)$
      end if
    end for
scheduled-load(1,:) = popnew(1,i)
    if $scheduled - load_i == 1$ **then**
      $\tau_{lot} = \tau_i - 1$
    end if

  end if
Generate new population. Select crossover pair a, b
  if $P_c > rand$ **then**
    $crossover(a, b)$
  end if
  if $P_m > rand$ **then**
    $mutate(a, b)$
  end if
popnew(popsize,N)
end for

on-site RES which can be utilized during peak hours to reduce electrify cost. Each home is equipped with various types of loads having different power ratings and variable duty cycles (table 1). The optimization program runs for a complete day where $[t \in T]$ time slots are further divided into sub-time slots having equal length of one hour. The simulations are performed for two different cases: (i) load scheduling using market based clearing prices (i.e., TOU, RTP), and (ii) using individualized prices as discussed in section IV-D.

Algorithm 2 Centralized EMC Algorithms

1: **Required** Scheduled pattern from distributed EMC, population size, max. generations, N, ψ.
2: Initialize random population which represents the patterns of appliances and $t = 1$.
3: Calculates k on the basis of distributed EMC energy consumption data using Eq. (9).
4: Evaluate φ for each user $u \in U$ using Eq. (10).
5: Communicates this new φ to its respective user $u \in U$.
6: Evaluate fitness function using Eq. (15).
7: From step 6, select optimal pattern which satisfies Eq. (14a-14e) and (15b-15d) .
8: Turn *ON* the loads according to optimal pattern and calculates τ and Ω for the next evaluation.
9: Generates new population to calculate fitness until convergence criteria is met.
10: $t = t + 1$, go to step 3, till $t = 24$.

The former one uses traditional RTP signal taken from [43] and is shown in Fig. 7. Then on the basis of RTP signal, algorithms solve load management problem [6], [7], [44], [61], [62], [78] to minimize electricity cost and high peaks on grid side. Although the traditional energy management mechanisms work on the basis of price based DR programs and are efficient for cost, comfort and grid stability. But, the discriminatory price policies do not ensure the consumers' savings. In contrast, the proposed work uses non-discriminatory prices which are calculated as described in section IV-D. These cases clearly depict the impact of individualized prices on electricity cost of end users. Then the final optimization program is solved by using GA providing the optimal results given in table 2. As the load optimization problem is well behaved. So the existing optimization engine is sufficient for the numerical solution. The MATLAB (Matrix Laboratory) language is used to solve the problem with the objective of cost minimization. The code was executed on Macbook Laptop, 1.7GHz Intel Core i7 processor.

VIII. RESULTS AND DISCUSSIONS

Fig. 9 shows the energy consumption profile of all users over the period of 24 h. The optimization program successfully solves the load scheduling problem in response to respective constraints fulfilling the energy demand. In case of $U1\&U2$, the energy source provided by retailers acts as "first choice" coming into operation to fulfil the energy demand. However in case of $U3$, the RES acts as first choice to fulfil energy demand. If the energy demand during particular hours exceeds, the main energy source is then utilized. In unscheduled case, optimization algorithm schedules the loads without considering associated constraints. In response, the load is even turned ON during peak hours (i.e., 10:00-12:00h, Fig. 9). It is worth noting here that the energy consumption of $U3$ is comparatively less due to RES integration. In scheduled case, optimization program turns ON the load in various time

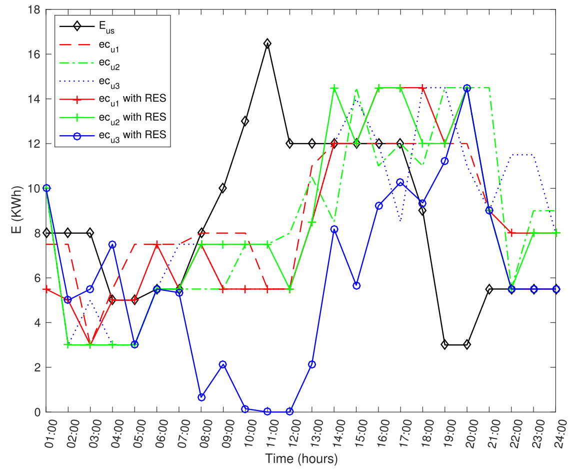

FIGURE 9. Energy consumption profile of all users over 24 h period.

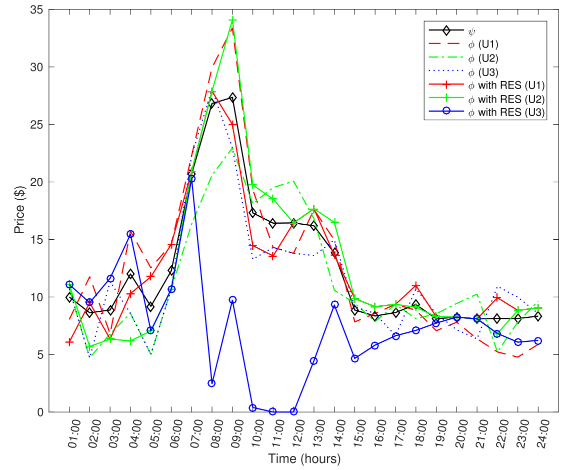

FIGURE 11. Individualized prices for all users over the period of 24 h (Eq. 9).

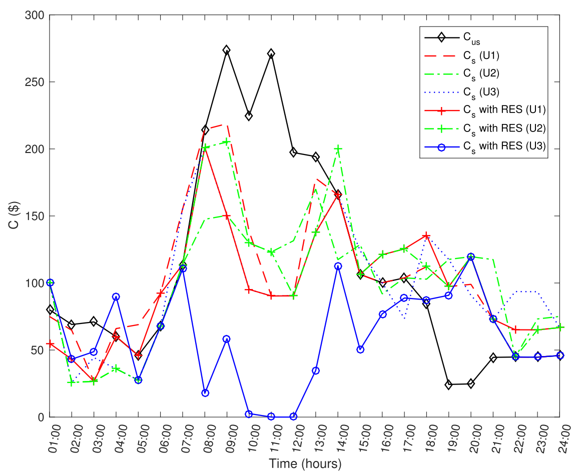

FIGURE 10. Cost incurred by different users over the period of 24 h using OP.

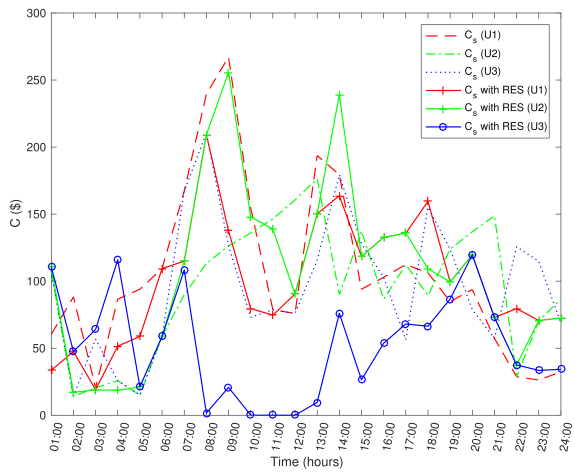

FIGURE 12. Cost incurred by different users over the period of 24 h using NP.

slots and avoids the peak hours. The total cost of $U1\&U2$ seems lower during 1:00-06:00h (Fig. 10). The average cost during 07:00-15:00h is comparatively high then the cost during 1:00-06:00h. From 16:00-24:00h, again the average cost of $U1\&U3$ is almost same. While the electricity cost of $U3$ during all hours is less. The reason behind reduced cost is the integration of on-site RES. These typical results originate form the fact that optimization algorithm follows the maximum energy consumption limit Eq. (14b) leading to significant reductions in hourly cost. In doing so, it is obvious that scheduled cost is always less than unscheduled cost alongwith utility objective i.e., reduced PAR.

Figs. 11 and 12 elucidate another case where energy prices are calculated on the basis of proposed mechanism discussed in section IV-D. For validation purpose, the energy consumption patterns given in (Fig. 9) remain same. However, the cost incurred by different users is different. This is because the individualized electricity prices are calculated on the basis of energy consumed by each user. t is also discussed in section IV-D that the individualized prices of all users depend on factor k. While the other energy management mechanisms use market based pricing signal irrespective to the energy consumption patters. So, prior to the calculation of electricity in case of traditional and proposed mechanisms, first we compute DR signals for all users on the basis of load consumed in $[t-1]$ h. Fig. 11 shows the individualized prices for all users over the period of 24 h. As a first observation, the electricity prices seem different/fluctuating, which show their dependency on individualized demand. In other words, these prices are calculated on the basis of individualized demand patterns in associated units. As the energy consumption patterns of $U3$ seems lower (Fig. 9). Consequently, the individualized price signal is comparatively low.

Fig. 12 further demonstrates the cost of residential units in terms of individualized energy consumption patterns over the period of 24 h. In early morning 01:00-6:00h, it is observed that the average cost using proposed method $(C_s(U_1), C_s(U_2), C_s(U_3))$ with RES is comparatively lower. This is due to the fact that individualized prices depend on the energy consumption pattern of each home, rather than aggregated energy demand. While during 07:00-14:00h, electricity cost of all users except $U3$ is much higher due to

TABLE 2. A comparison of electricity cost using OP and NP.

Users	Without RES				With RES			
	Total load (kW)	Cost-OP ($)	Cost-NP ($)	% age	Total load (kW)	Cost-OP ($)	Cost-NP ($)	% age
U1	201.50	2337.08	2306.08	-1.34	201.50	2363.40	2491.10	+5.12
U2	201.50	2415.08	2470.04	+2.22	201.50	2437.60	2569.20	+5.12
U3	201.50	2337.04	2313.08	-1.03	139.03	1349.90	1090.60	-23.77
Total	604.50	7089.02	7089.02	–	542.03	6150.90	6150.90	–

OP=Old Price, NP=New Price.

TABLE 3. A comparison of proposed results with some relevant works.

Reference	Pricing Technique	Optimization Technique	Objective	Limitation	Comparison
[48]	Individualised price policy	DAPP algorithm	Rebound peaks and average cost minimization	Price is calculated based on historical demand, while the demand is dynamic. For RTP, which is not known in advance, it seems infeasible	(2.08&5.32%), peak demand minimization
[49]	TOU and Customized prices	MINLP	Customized electricity retail prices based on end users' load features	Proposed price is based on historical load demand, while the actual demand is dynamic. So, there could be variation in price levels	4% peak load minimization
[50]	Uniform pricing approach	Greedy and Sliding-Window	Peak demand is minimized & power demand matches the supply	Energy loss problem, as compared to TOU pricing mechanism. It means, τ_{lot} problem is there	(1.3–9%) peak demand minimization, depending on W
[1]	TOU	Monte Carlo and numerical search	Minimize the mean electricity price	Focus is to determine TOU pricing based contract capacities. Customer centric approach	(7.23-7.73%) reduction in end users' cost
[2]	Market price signal	Dynamic aggregate model based on threshold policy	Prediction of the aggregate response of a large number of individual loads	Supply-demand mismatch as some loads are deferred to minimize cost	–
[63]	DAHP	Stackelberg game theory	Reduces user anxiety of price uncertainty	TOU and CP performed worse due to flexibility problem	10.7%>TOU and 10.17%>CP
Proposed	RTP based proposed price policy	Binary GA	Minimized cost, less chances of rebound peaks, supply-demand balance	CMS between utility and consumer is required Fig. 1. Extra cost and computational burden	See results in Table 2

DAHP=Day ahead hourly price, CP=Critical price, CMS=Community management system.

high individualized electricity prices (Fig. 11). It can also be seen that electricity cost of $U3$ is comparatively less due to incorporation of RES. In traditional case (Fig. 10), $U3$ incurs more cost during 7:00-10:00h. While, the cost in proposed scheme is comparatively lower. Therefore, the cost reductions can be attained if the value of the k is lower, which is demand dependant. Finally, table 2 shows the net revenue obtained by utility in centralized and distributed algorithms. It is evident from the table that using proposed scheme, the utility objective remains same. However, the individualized users may take benefits if they are consuming less energy. Another important aspect of the proposed scheme is that the prices are calculated on hourly basis. In other words, if any user is consuming more energy e_1 in h_1 hour, that user will be charged the price according to the proposed mechanism. The role of *OP* and *NP* schemes is further demonstrated in table 2 which gives the comparison of energy consumption and electricity cost. In case when RES is not utilized, the electricity cost of $U1\&U3$ using *NP* is reduced. While the electricity cost of $U2$ is 2.22% increased. This is due to high value of k. While the rest of the users $U1\&U3$ consumed 1.34% and 1.03% less energy and consequently, they receive less bill. In contrast when RES is incorporated in $U3$, then the energy demand is primarily fulfilled by using RES. If the energy demand exceeds from RES capacity, the grid energy is then utilized as a secondary choice. It is worth noting here that the value of k (Eq. 9) depends on energy consumption factor which ultimately changes the electricity cost. So the variation in k gives 5.12% more electricity cost in case of $U1\&U2$. Furthermore, the total amount of energy obtained form grid is also reduced by 11.52% when RES is used contributing towards grid stability. Hence it is demonstrated that the individualized prices depend on the energy consumption patterns of all users/homes.

Finally, the table 3 provides a comparison of proposed work with counterpart techniques regarding cost and peak load minimization. Work reported in [46]–[48] used different pricing policies for peak load minimization, through optimized load scheduling. Similarly, the work presented in [1], [61] significantly minimized end user cost when load is scheduled in accordance with other than market clearing prices such as TOU and CP. However, the proposed work focusses on devising price profiles for all users such that each user must be provided a separate price signal based on demand consumption and RTP obtained directly from electricity market. Unlike other works, the proposed work focusses to provide a mathematical model to construct load dependant cost profiles rather than minimize the end user cost through optimized load patterns. However, in order to provide the justification of obtained achievement, we used a GA to obtained optimal load patterns, so as to compare the cost against unscheduled case as shown in Table 2.

IX. CONCLUSION

In this paper, we have proposed a novel pricing mechanism for demand management using individualized price policies in conjunction with energy demand, electricity price and RES to incentivise low energy users. The major contribution of this work is to facilitate low energy consumers by providing incentives in the form for reduced electricity bill. In addition, electricity cost is reduced in such a way that high peaks are also reduced while maintaining the utility revenue, even though the individualized prices are non-discriminatory. For true analysis, the results of the proposed scheme are compared to the traditional scheme where price based DR signal is used by the consumers operated under same DSO. The analysis conducted in this paper illustrates the advantages of the individualized prices thorough extensive simulations considering the data given in table 1. It was also demonstrated in section VIII that the proposed scheme distributes electricity prices among all users/units on the basis of load consumed while keeping utility objectives high. The further cost reductions can be obtained if the coordination among all the users are incorporated. This objective can easily be achieved using multiagent technology. So, in future, we will use multiagent technology for real time coordination and control to further reduce the energy consumption costs of individualized users.

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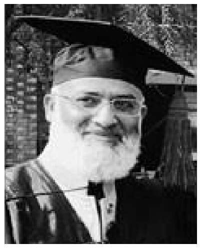

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