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Minimizing pricing policies based on user load profiles and residential demand responses in smart grids

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ABSTRACT

This paper considers the time of use (TOU) pricing scheme to propose a consumer aware pricing policy (CAPP), where each customer receives a separate electricity pricing signal. These pricing signals are obtained based on individualized load demand patterns to optimally manage the flexible load demand. The main objective of CAPP is to reduce the peaks in overall system demand in such a way that the pricing signals remain non-discriminatory. To achieve this goal, firstly the mathematical model of CAPP comprising TOU electricity price, and its variation based on consumption patterns is formulated. Secondly, the proposed CAPP model is further extended by integrating renewable energy and storage sources to overcome the possible creation of rebound peaks due to scheduling. This objective is achieved by implementing a control variable modeling the upper bound of the low tariff area. Thirdly, the cost minimization optimization problem is solved by using a Genetic Algorithm (GA) with the objective of the fair price distribution. Numerical and simulation results are obtained to validate the proposed model in terms of convergence, optimality, and cost reduction objective function. Results reveal that each customer receives a separate electricity price signal based on his demand pattern without affecting the utility/retailer revenue. Furthermore, the total cost results are also compared with and without TOU & CAPP schemes to further validate the nondiscrimination in electricity price.

1. Introduction and background

Optimal utilization of energy generation resources is one of the pressing challenges facing today's power sector. Because, due to the ever-increasing world population and the rapid development in the information and communication technology (ICT) industry, the energy demand increases, substantially [1]. In contrast, the power generating and transmitting capability of the current power system is increasing at a much slower pace. This is due to the capacity limits on conventional power generation resources since thermal power generation is not very popular due to carbon dioxide emissions [2]. Therefore, the development of load scheduling schemes with efficient utilization of available energy resources with the integration of renewable energy is required to the ongoing collective prosperity and quality of life [3–5]. For this purpose, it is needed to consider the activities or programs to promote the reduction in energy consumption and management of end-user loads. The former considers efficient building materials [6,7] and smart loads [8]. The latter focuses on the development of efficient load scheduling and optimization techniques [9,10]. To overcome the aforementioned limitations and problems, the smart grid (SG) has introduced demand response (DR) as a key enabling program for the end-users to manage their loads. Generally, the direct load control (DLC) and dynamic DR schemes are widely adopted in developing energy management programs [11,12]. Although the DLC scheme is useful in increasing the grid stability, however, this may affect the social welfare and comfort of consumers [13]. Thus, with variable load and load consumption profiles, the DLC is rather used as a passive scheme. In contrast, the DR programs are explicitly designed for residential consumers to reschedule their loads [14]. As, the DR schemes are quite efficient, however, for long-term residential energy management, the uncertainties in the load demand, electricity price, and renewable energy resources need to carefully be addressed. Otherwise, the utilities and the end-users in particular, may be improperly charged. As a result, this may discourage the end-users in adapting and participating in DR programs for mutual benefits such as reliability and cost reduction [15]. Because the electricity tariff in electricity retail market is designed based on aggregated load [16], it seems very difficult to design these tariffs for the individual or homogeneous[2] users. Eventually, the customers who have maintained a balanced load profile aiming at reducing

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[2] It defines those customers who have maintained balanced load demand profiles to avoid rebound peaks.

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Nomenclature

β	Binary decision variable
$\mathbb{E}_{c,i}$	Expected electricity cost of ith users
λ	Denotes the threshold value for CAPP
μ	Utility cycle denoting load operating interval
$\overline{p_{d_i}}$	max. load demand of ith user
$\overline{p_{PV_i}(t)}$	max. limit on power obtained from PV source over time t
$\overline{p^{act}_{PV_i}}(t)$	max. limit renewable power from PV source of ith user over time t
$\underline{p_{d_i}}$	min. load demand of ith user
$\underline{p_{PV_i}(t)}$	min. limit on power obtained from PV source over time t
φ	Electricity price signal
φ_t^{hp}	High-peak price over the time slot t
φ_t^{lp}	Low-peak price over the time slot t
φ_t^{op}	Off-peak price over the time slot t
$\varphi^{PV}(t)$	Pricing signal for PV over time t
$\varphi^{s}(t)$	Pricing signal for storage over time t
$\varphi^{TOU}(t)$	TOU pricing signal over time t
$\varphi_{CAPP,i}$	Electricity price profiles using CAPP
$c_i(t)$	Total energy cost of ith user over t
$c_{CAPP,i}$	Electricity cost of ith user using CAPP
c_g	Energy consumption cost of grid energy
$c_{p_{d,i^{un}}}(t)$	Cost of unscheduled load of ith user over t
$c_{p_{d_i^{sch}}}(t)$	Cost of scheduled load of ith user over t
d	Index for a day
$f(.)$	Random generation function
i	Index for residential users
m	Index for a month
p_d	Total load demand
p_g	Power obtained from electric grid
p_s	Power stored in energy storage system
$p_{d_i^{sch}}$	Scheduled load demand of ith user
$p_{d_i^{un}}$	Unscheduled load demand of ith user
p_{d_i}	Load demand of ith user
p_{PV}	Power obtained from photovoltaic source
$p^{act}_{PV_i}(t)$	Actual renewable power from PV source of ith user over time t
t	Index for time horizon
U	Index for total number of users

their electricity bills may be overcharged. This is due to other customers who have not willingly participated in DR programs and overconsumed the load, even during peak hours [17]. Hence, based on unfair price distribution problems in existing schemes, this work provides a novel pricing policy that can be used as a benchmark for other retailers and policymakers.

The paper is structured as follows. Section 2 provides recent literature, relevant to the topic. Section 3 motivates the work and its main contributions. A description of the system model is presented in Section 4. Then, Section 5 presents the results. Finally, conclusions are outlined.

2. Literature survey

In the literature, various energy management mechanisms using market-clearing prices and DR strategies [18,19] have been discussed with the objectives of; electricity cost reduction of end-users [20], peak shaving with load balancing [21,22] and user comfort maximization [23,24]. Among these mechanisms, the major attention is given to maximize the benefits of the utility and users through the encouragement of active participation in DR programs. Mohandes et al. [25] propose a novel compensation scheme based on DR programs for load curtailment within the defined window. A piece-wise reward function based on two intervals to provide the incentives to the users is used. To maximize the end-user reward, the small contracts are designed and optimized to maximize social welfare. The objective function is formulated as a mixed-integer linear programming that is solved using the decomposition method. The work demonstrated by Huang et al. [18] is used to schedule multi-energy industrial load with photovoltaic and battery storage systems. The objective function is formulated as a scenario-based stochastic non-convex mixed integer nonlinear programming with the objective of operational cost minimization of the production facility. Wang et al. [19] propose an integrated demand response mechanism to minimize the operating cost of the energy system. An interval method to analyze the uncertainty of integrated demand response is used. This method is effective in cost-saving and load response effects when compared with robust methods. However, due to a lack of uncertainty analysis, its performance is not well justified. Ding et al. [26] develop a real-time locational marginal pricing-based on DR programs to track the real equilibrium points. The load demand is modeled as a monotonously decreasing linear function, which is difficult to solve in the presence of primary and dual variables. Therefore, the problem is decomposed into a convex quadratic problem using duality theory. Without modeling the uncertainties involved in finding the equilibrium points, the results may vary. The work demonstrated by Al-Rubaye et al. [27] show a dynamic electricity pricing mechanism using an SG communications network. Another dynamic pricing mechanism is developed for trading-off between the end-user and utility regarding profit maximization [28]. It allows the market operators to purchase power from different producers and to set the tariff based on the demand–supply theory of economics. In this work, the users are not allowing maximizing their comfort or profit. However, both homogeneous and non-homogeneous customers still need to be charged based on load consumption patterns instead of pricing information obtained using forecasting algorithms. The work reported by Lu et al. [29] propose a reinforcement learning-based decision support system for an individual user to select an optimal electricity pricing plan offered by retailers. For this purpose, the problem is formulated as a Markov decision process without a transition probability. Then, based on the energy demand requirement of any user, the decision support system selects the optimal pricing plans to minimize the cost and dissatisfaction through prior incentives and rewards. Furthermore, this work handles the uncertainties through the Q-learning algorithm for good results. Although this work has increased user satisfaction, however, if the user demand varies after the selection of optimal pricing plan, then the user satisfaction could be affected. Yang et al. [30] use a density-based spatial clustering algorithm to extract load consumption patterns of various users from historical data. Then, based on load profiles and price levels, the retail prices are constructed to reduce the energy consumption cost of users with comparatively higher consumption levels. For matching supply–demand and peak load management, threshold-based price policies under a dynamic environment have been proposed [31]. Initially, different price thresholds have been assigned over the given time intervals to reduce peak demand. Then, prices are designed in such a way to match energy demand and supply. A novel pricing model is used to devise customized TOU prices by taking into consideration load variations [32]. These variations are observed due to randomized load consumption patterns, therefore, the Monte Carlo method is used to obtain smooth load patterns. Al-Rubaye et al. [27] propose a dynamic electricity pricing scheme by taking into consideration real-time price (RTP) and load demand. This work significantly reduces the utility prices for consumers along with a balanced load curve. However, the customers showing balanced load profiles over given time intervals are provided with the electricity tariff under aggregated load consumption. Perhaps, it seems difficult for energy retailers to construct separate unit tariffs for each customer. It may otherwise create a high communication burden through massive data exchanged between users and utility. On the other hand, the excessive use of conventional energy generation resources may raise climate-related concerns. To handle such types of issues, a control mechanism to manage the energy resources without heavily relying on the conventional generation facilities is sought. For this purpose, the researchers have used the autonomous load management mechanisms [33]. The work demonstrated by Konda et al. [34] has integrated the solar and wind energy resources into the current energy system to meet the variable energy demand with reduced carbon emissions. In addition, the work presented by Rana et al. [35] shows that through renewable energy integration and electrification transportation, the load demand can be efficiently managed. However, in the case of autonomous energy management, an SG technology is being adopted which allows the energy retailers, prosumers, and market participants to manage the energy demand using price-based DR mechanisms. However, to get the full advantage of DR programs, the customers need to adopt and participate. This, however, could be possible to encourage the customers to participate through various incentives. These incentives could be in the form of bill reduction or comfort maximization [36–38].

3. Motivation

From the literature review, it is observed and analyzed that there are numerous energy management mechanisms and algorithms that are being designed based on price-based DR programs such as; RTP, TOU, and day-ahead pricing [39]. Few among these mechanisms focused on the cost reduction [40], while the others are designed to minimize the cost and user dissatisfaction. However, in the case of electricity cost reduction, there could be chances of high or rebound peaks during low pricing hours [37]. The reason is that the consumers intend to turn on the heavy loads with the primary objective of bill reduction due to low pricing tariff [41]. In contrast, the other users have maintained stable load demand profiles and may be priced unfairly. This particular problem is due to the nature of price-based DR programs as they are designed based on aggregated load demand, instead of the load profile of each user [42]. Consequently, the users having a balanced load profile need to be priced in a way that other customers may not get affected due to the electricity tariff. Therefore, by taking into consideration this particular issue, the proposed pricing policy is designed which is nondiscriminatory (Section 4.3.1). Thus, based on the aforementioned explanation, the proposed work intends to develop a dynamic pricing mechanism that considers the load demand profiles of all the users. The novel aspect of this work is that the utility revenue remains balanced, even if the n users participate in the load management programs (Section 4.3 (proposition)). The real contributions of this work are discussed as follows. A novel electricity pricing mechanism “CAPP” based on the individualized load consumption patterns and electricity price information is proposed. The RTP and aggregated load demand information can be directly obtained from smart meters [43] using the SG communication infrastructure. Firstly, the mathematical models of load consumption, renewable energy integration, and electricity cost calculation are presented. Then the CAPP is described where the individualized load consumption patterns, RTP signal and renewable energy capacity are considered as input parameters. Finally, a constraint optimization problem is formulated, which is solved by using a GA with the objective of electricity cost reduction with higher end-user comfort. In this work, the user comfort is modeled in terms of a fair price distribution among all the customers in such that the prices must be non-discriminatory/homogeneous (Section 4.2).

Table 1
Total number of users and respective loads in (kW).

Users	[Load]					
	1	2	3	4	5	6
1	2.5	3.0	2.0	2.5	3.5	3.0
2	1.5	2.0	2.5	3.5	3.0	1.0
3	3.5	1.5	2.0	2.5	3.7	3.0

4. System model

This proposed system model shown in Fig. 1 builds upon the same model used by Al-Rubaye et al. [27]. However, the proposed model is designed to find the CAPP based on TOU pricing and load demand patterns obtained from smart meters via advance metering infrastructure (AMI). Let residential user $i \in U$ is equipped with sources of; grid power ($p_g(t)$), photovoltaic (PV) power ($p_{PV}(t)$) and/or energy storage $p_s(t)$ systems. Due to the intermittent nature of renewable energy, the value of $p_s(t)$ is subject to charge and discharge of storage. Subsequently, the storage value is subject to usage. Let, $t \in T$ denotes a billing period of 24 equally spaced time slots (e.g., t_{03} denotes third time slot, Fig. 2), load types over given time t are given in Table 1, and β depicts a binary decision variable used to denote ON/OFF states of connected loads. Please note that the data used in Table 1 is only considered for implementation and validation of the proposed pricing policy. However, any data set can be used for detailed analysis. Let φ denotes the price information which can be directly received from an electricity market via AMI.

Generally, the price function is load dependent which is hourly updated based on load demand profiles obtained from smart meters. To ensure the uninterrupted supply of energy demand even during critical hours, real-time exchange of information between utility and consumer is required. In this work, a customized price function comprising load and price components is obtained over 24 h [27,44]. Let the net power obtained from the grid over the t period be defined as in the work of Al-Rubaye et al. [27]:

$$p_{g,i}(t) = \sum_{t=1}^{T}\sum_{i=1}^{U}\Big(p_{d,i}(t) - \big(p_{PV,i}(t) + p_{s,i}(t)\big)\Big) \tag{1}$$

The respective cost as per energy consumption function based on TOU pricing signal is depicted in Eq. (1) is given as:

$$c_{g,i}(t) = \sum_{t=1}^{T}\sum_{i=1}^{U}(p_{d,i}(t)\varphi^{TOU}(t) - (p_{PV,i}(t)\times\varphi^{PV}(t) + p_{s,i}(t)\times\varphi^{s}(t))) \tag{2}$$

where, $\varphi^{PV}(t)$ and $\varphi^{s}(t)$ denote the cost of solar energy and storage system, respectively. In the proposed work, the $\varphi^{s}(t)$ is considered unity per unit. While, according to national renewable energy laboratory (NREL), the cost of PV energy can be calculated using the following expression [45,46]:

$$\varphi^{PV}(t) = \frac{\sum_{t=1}^{T}\dfrac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{T}\dfrac{I_t + M_t + F_t}{(1+r)^t}} \tag{3}$$

where, I_T, M_t, F_t denote investment, maintenance and fuel expenditures. While, r and n denote discount rate and expected lifetime of the PV system. Generally, the total cost of PV based system is calculated over the lifetime of a system in KW/h or MW/h. However, the present work is dedicated only to find a user eccentric price policy and does not consider the renewable energy generation or installation cost. Thus, the $\varphi^{PV}(t)$ value is considered unity per unit for implementation.

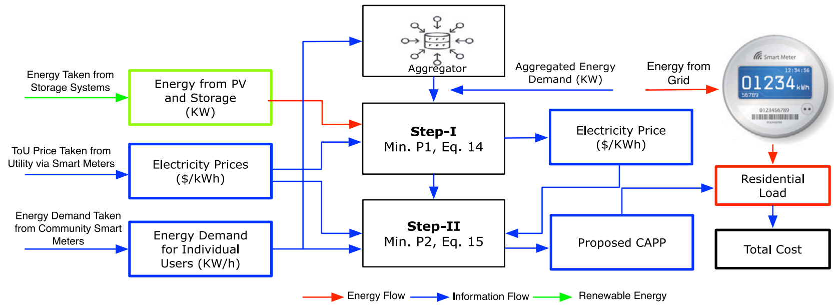


Fig. 1. Proposed system model.

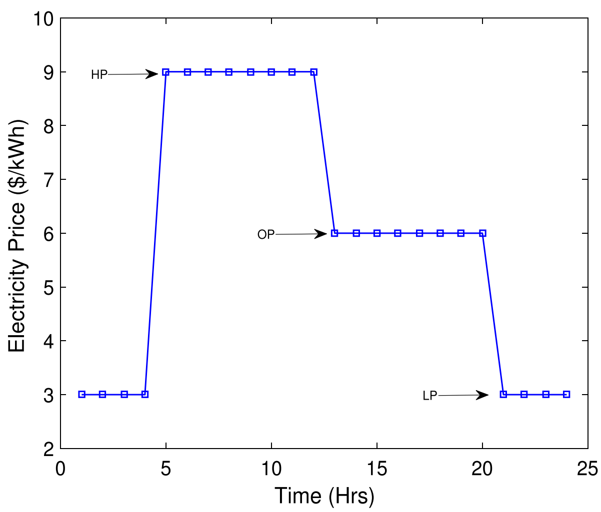


Fig. 2. Electricity price signal defined by Al-Rubaye et al. [27].

4.1. Traditional model

This section demonstrates the traditional pricing mechanism being widely used in the literature [47–49]. Generally, the energy retailers in the electricity market devise the tariff based on aggregated load demand data, which is obtained from the advanced metering infrastructure [26,50,51]. Where the seasonal electricity prices such as TOU can be fixed for the short or medium time intervals. However, the day ahead TOU and RTP depend on the real-time load consumption patterns. In response, the customers who participate in the load management programs based on DR may get monetary incentives in terms of bill reduction through load shifting during peak-demand hours. In contrast, the customers who are unaware of the DR programs and unwilling to participate in the load management may not be able to get any incentive except high comfort. Here, the comfort is provided in terms of an uninterruptible power supply even during on-peak hours. Hence, the trade-off between cost and comfort exists, which is difficult to achieve. The load cost of user i over time t (i.e., day ($t \in d$)) subject to predefined load demands can be calculated as [27]:

$$c_{i,d} = \sum_{i=1}^{U} \Bigg(\sum_{t\in t_{21}\cup t_{04}} (\beta p_{d,i}(t))\varphi_d^{op}(t) + \sum_{t\in t_{05}\cup t_{12}} (\beta p_{d,i}(t))\varphi_d^{lp}(t) + \sum_{t\in t_{13}\cup t_{20}} (\beta p_{d,i}(t))\varphi_d^{hp}(t) \Bigg) \tag{4}$$

$$\varphi(t) = \begin{cases} \varphi^{hp}(t) > \varphi^{lp}(t) \\ \varphi^{lp}(t) > \varphi^{op}(t) \\ \varphi^{hp}(t) > \varphi^{op}(t) \end{cases} \tag{5}$$

where, the expression (5) depicts the pricing priorities, and $\varphi^{hp}, \varphi^{lp}, \varphi^{op}$ denote pricing periods for off-peak price (op) $t_{13:00-20:00}$, high-peak price $(hp\ t_{04:00-12:00}$ and low-peak (lp) $t_{20:00-23:00,00:00-04:00}$ price regions, respectively. It is also worth mentioning here that these price periods depict the TOU pricing trends, rather than RTP which may vary the following time. Similarly, energy consumption cost over a month $(t \in m)$ period for all consumers is given as:

$$c_{i,m} = \sum_{i=1}^{U} \Bigg(\sum_{t\in t_{21}\cup t_{04}} (\beta p_{d,i}(t))\varphi_m^{op}(t) + \sum_{t\in t_{05}\cup t_{12}} (\beta p_{d,i}(t))\varphi_m^{lp}(t) + \sum_{t\in t_{13}\cup t_{20}} (\beta p_{d,i}(t))\varphi_m^{hp}(t) \Bigg) \tag{6}$$

The total cost over a m time period for users U, using historical data is given as:

$$c_{i,m} = \sum_{i=1}^{U} \Bigg(\sum_{t\in t_{21}\cup t_{04}} (\beta p_{d,i}(t))\varphi_m^{op}(t) + \sum_{t\in t_{05}\cup t_{12}} (\beta p_{d,i}(t))\varphi_m^{lp}(t) + \sum_{t\in t_{13}\cup t_{20}} (\beta p_{d,i}(t))\varphi_m^{hp}(t) \Bigg) \tag{7}$$

In this work, three users $U = 3$ have been considered for implementation and validation of the proposed cost calculation mechanism. However, the value of U can be varied as per the given requirement. The expression to calculate CAPP over the day d time period is given below (Eq. (8))

$$\begin{aligned} c_{i,d} = \sum_{i=1}^{U} \Bigg[& \Bigg(\sum_{t\in t_{21}\cup t_{04}} \beta p_{d,i}(t) \Bigg((\beta p_{d,i}(t)) \Bigg[\frac{\sum_{t\in t_{21}\cup t_{04}} p_{d,i}(t)\varphi_d^{lp}(t)}{p_{d,i}^2(t)} \Bigg] \Bigg) \Bigg) + \\ & \Bigg(\sum_{t\in t_{05}\cup t_{12}} \beta p_{d,i}(t) \Bigg((\beta p_{d,i}(t)) \Bigg[\frac{\sum_{t\in t_{05}\cup t_{12}} p_{d,i}(t)\varphi_d^{op}(t)}{p_{d,i}^2(t)} \Bigg] \Bigg) \Bigg) + \\ & \Bigg(\sum_{t\in t_{13}\cup t_{20}} \beta p_{d,i}(t) \Bigg((\beta p_{d,i}(t)) \Bigg[\frac{\sum_{t\in t_{13}\cup t_{20}} p_{d,i}(t)\varphi_d^{hp}(t)}{p_{d,i}^2(t)} \Bigg] \Bigg) \Bigg) \Bigg] \end{aligned} \tag{8}$$

Similarly, the expression to calculate CAPP over the month m time period is given below:

$$\begin{aligned} c_{i,m} = \sum_{i=1}^{U} \Bigg[& \Bigg(\sum_{t\in t_{21}\cup t_{04}} \beta p_{d,i}(t) \Bigg((\beta p_{d,i}(t)) \Bigg[\frac{\sum_{t\in T}\sum_{i=1}^{U} p_{d_i}(t)\varphi_m^{lp}(t)}{p_{d,i}^2(t)} \Bigg] \Bigg) \Bigg) + \\ & \Bigg(\sum_{t\in t_{05}\cup t_{12}} \beta p_{d,i}(t) \Bigg((\beta p_{d,i}(t)) \Bigg[\frac{\sum_{t\in T}\sum_{u=1}^{U} p_{d,i}(t)\varphi_m^{op}(t)}{p_{d,i}^2(t)} \Bigg] \Bigg) \Bigg) + \\ & \Bigg(\sum_{t\in t_{13}\cup t_{20}} \beta p_{d,i}(t) \Bigg((\beta p_{d,i}(t)) \Bigg[\frac{\sum_{t\in T}\sum_{i=1}^{U} p_{d,i}(t)\varphi_m^{hp}(t)}{p_{d,i}^2(t)} \Bigg] \Bigg) \Bigg) \Bigg] \end{aligned} \tag{9}$$

The expression to calculate monthly cost for U users over an m time period considering renewable system is expressed as:

$$\begin{aligned} c_{i,m} = \sum_{i=1}^{U} \Bigg[\Bigg(& \sum_{t\in t_{21}\cup t_{04}} \beta p_{d,i}(t) - p^{act}_{PV_i}(t) \\ & \times \Bigg((\beta p_{d,i}(t) - p^{act}_{PV_i}(t)) \Big[\frac{\sum_{t\in T}\sum_{i=1}^{U}(p_{d_i}(t) - p^{act}_{PV_i}(t))\varphi^{lp}_m(t)}{p^2_{d,i}(t)} \Big] \Bigg) \Bigg) \\ & + \Bigg(\sum_{t\in t_{05}\cup t_{12}} \beta p_{d,i}(t) - p^{act}_{PV_i}(t) \\ & \times \Bigg((\beta p_{d,i}(t) - p^{act}_{PV_i}(t)) \Big[\frac{\sum_{t\in T}\sum_{i=1}^{U}(p_{d,i}(t) - p^{act}_{PV_i}(t))\varphi^{op}_m(t)}{p^2_{d,i}(t)} \Big] \Bigg) \Bigg) \\ & + \Bigg(\sum_{t\in t_{13}\cup t_{20}} \beta p_{d,i}(t) - p^{act}_{PV_i}(t) \\ & \times \Bigg((\beta p_{d,i}(t) - p^{act}_{PV_i}(t)) \Big[\frac{\sum_{t\in T}\sum_{i=1}^{U}(p_{d_i}(t) - p^{act}_{PV_i}(t))\varphi^{hp}_m(t)}{p^2_{d,i}(t)} \Big] \Bigg) \Bigg) \Bigg] \end{aligned} \tag{10}$$

Similarly, the expression to calculate monthly cost for U users over an m time period considering renewable and storage systems is expressed as:

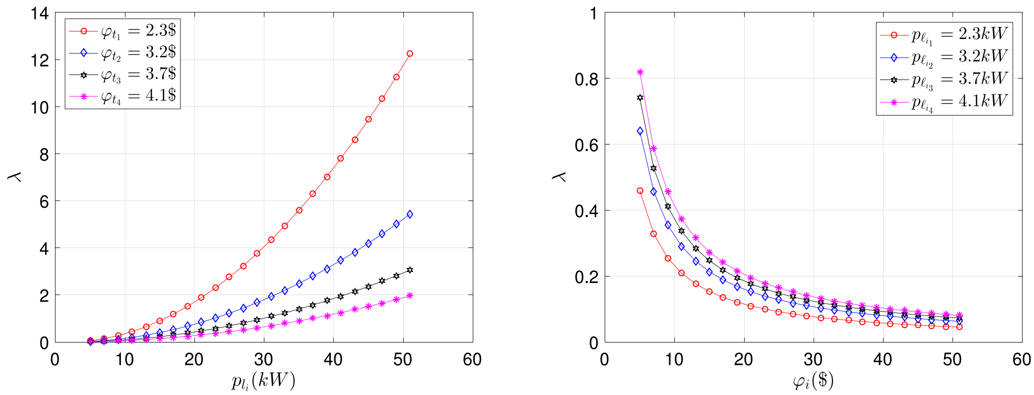
$$\begin{aligned} c_{i,m} = \sum_{i=1}^{U} \Bigg[\Bigg(& \sum_{t\in t_{21}\cup t_{04}} \beta p_{d,i}(t) - (p^{act}_{PV_i}(t) + p_s(t)) \Bigg((\beta p_{d,i}(t)) - \\ & (p^{act}_{PV_i}(t) + p_s(t)) \\ & \Big[\frac{\sum_{t\in T}\sum_{i=1}^{U}(p_{d_i}(t) - (p^{act}_{PV_i}(t) + p_s(t)))\varphi^{lp}_m(t)}{p^2_{d,i}(t)} \Big] \Bigg) \Bigg) \\ + \Bigg(& \sum_{t\in t_{05}\cup t_{12}} \beta p_{d,i}(t) - (p^{act}_{PV_i}(t) + p_s(t)) \Bigg((\beta p_{d,i}(t)) - \\ & (p^{act}_{PV_i}(t) + p_s(t)) \\ & \Big[\frac{\sum_{t\in T}\sum_{i=1}^{U}(p_{d,i}(t) - (p^{act}_{PV_i}(t) + p_s(t)))\varphi^{op}_m(t)}{p^2_{d,i}(t)} \Big] \Bigg) \Bigg) \\ + \Bigg(& \sum_{t\in t_{13}\cup t_{20}} \beta p_{d,i}(t) - (p^{act}_{PV_i}(t) + p_s(t)) \Bigg((\beta p_{d,i}(t)) - \\ & (p^{act}_{PV_i}(t) + p_s(t)) \\ & \Big[\frac{\sum_{t\in T}\sum_{i=1}^{U}(p_{d_i}(t) - (p^{act}_{PV_i}(t) + p_s(t)))\varphi^{hp}_m(t)}{p^2_{d,i}(t)} \Big] \Bigg) \Bigg) \Bigg] \end{aligned} \tag{11}$$

4.2. Proposed CAPP

This section discusses the CAPP for all users, whether they have or have not participated in the load management program. The major focus is to devise a novel pricing mechanism for all types of customers, depending on their energy consumption patterns, that can be obtained from the advanced metering infrastructure [50]. Here, our objective is threefold: (i) initially, the electricity price depending upon load demand of each user has been calculated with the objective of fair cost distribution. The term fair cost distribution means that instead of using the RTP, each user will receive a separate electricity price signal based on his/her energy consumption pattern. Eventually, unlike the other customers, that used RTP, the electricity cost profile of each user would be different. However, the total cost remains the same. (ii) electricity price is calculated in such that total cost of i users who have maintained a balanced load profile is significantly reduced. (iii) the direct impact of the proposed price on the cost is also analyzed when combined grid and energy storage sources are used. Furthermore, to have customers agreeing on CAPP, these prices must be homogeneous, (i.e., prices must not affect other players). Otherwise, it would eventually decrease the total number of customers participating and accepting the proposed scheme. In our case, we can formally define price homogeneity in such a way that all prices are homogeneous if all participating customers have the equal opportunity to pay the low cost, irrespective of market limitations and peak hour prices. This is also feasible for those customers who do not want to participate in energy management programs. However, it is worth mentioning here that to calculate the proposed price, information about the traditional price calculation mechanism is required. And the reason is that we require the net power demand and electricity tariff to devise a new tariff for comparison and validation. Among all inputs being given to the control unit, the input "energy demand taken from community smart meters" explicitly explains that this information is obtained from the community management system (CMS) [52]. It is further assumed that CMS exists between consumers and the energy retailers, which ensures real-time data is exchanged between these entities. This is also since it seems infeasible for an energy retailer to provide a separate energy price signal to each consumer. Thus, to facilitate energy consumers without relying directly upon the retail market, CMS is introduced in each region operated under the same distributed system operator. Moreover, the expression to devise CAPP over a day is given in Eq. (8). The first part of this equation is used to calculate electricity cost during φ^{lp}. Similarly, the second and third parts of this equation are used to calculate the cost during φ^{op} and φ^{hp}, respectively. The energy consumption cost for U users over a month period m is expressed as Eq. (9). Finally, monthly billing cost for U users over an m period considering renewable and storage systems is expressed as Eqs. (10), (11). Fig. 3 shows the variations in λ in conjunction with p_{d_i}(kW) and φ_i($). We provide the numerical results to elaborate that with the increase in the value of φ_i($), the λ increases, which can be seen from Fig. 3a. In contrast, the value of λ is decreased with the increase in the value of p_{d_i}(kW) (Fig. 3b). It can be written (λ = threshold factor in ($)) in order to denote the expression $\frac{\sum_{t\in d} p_{d_i}(t)\varphi^{lp}(t)}{p^2_{d_i}(t)}$, which is used to calculate sub-optimal or individualized pricing profiles for all users over time t. Based on Eqs. (1)–(7), the energy consumption cost is calculated using TOU pricing signal. However, Eqs. (8)–(10) are used to find the cost based on λ. Where, λ denotes the variation in electricity price which depends on TOU and $p_{d,i}$. For example, Fig. 3a shows the relationship between λ and $p_{d,i}$. If the value of $p_{d,i}$ increases, the value of λ increases and vice versa. As a result, the c_i will eventually be increased. The similar trend can also be visualized in Fig. 3b. Please note that, these pricing policies are obtained based on TOU pricing signal obtained from electricity retail market. From these results, it can be concluded that CAPP is directly dependent on λ, which further depends on the energy demand and the electricity price variations. Intuitively, in case of high energy demand during particular hours, the respective users have to pay according to the load demand and the price information. In response, the homogeneous consumers are kept away from being overcharged. Thus, it is now obvious and proved from results that the proposed mechanism is used to distribute electricity prices realistically without disturbing utility and users objectives.

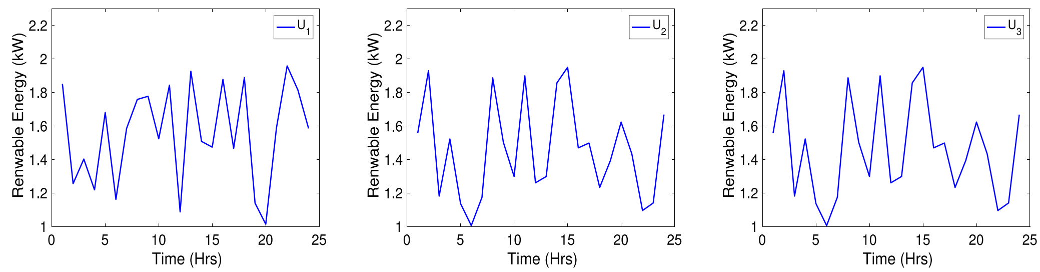
4.3. Renewable power generation model

This section builds upon the same model as described in Section 4.2, where the proposed mechanism for calculating energy consumption prices is discussed. Let $p^{act}_{PV_i}(t)$ denotes actual renewable energy obtained from solar photovoltaic source at time slot t for ith user such that $p^{act}_{PV_i}(t) > 0$. It is assumed that $p_{PV_i}(t)$ is predictable but with finite error due to randomness of associated parameters (i.e. solar irradiance or power loss). It is worth noting here that to analyze the impact of



(a) λ vs φ_i (b) λ vs p_{d_i}

Fig. 3. Impact of p_{d_i}(kW) and φ_i($) variations on the calculation of λ, used to devise CAPP over time t. (a) λ increases if the load demand increased. It means, the electricity price for this particular user will also be increased, (b) the value of λ decreases if the value of φ increased. It means if the electricity price decreases, the value of λ also decreases.



(a) RES for U_1 (b) RES for U_2 (c) RES for U_3

Fig. 4. The renewable energy source for each individual user over given time t. The optimal integration of the renewable energy sources to fulfill the load demand is done, where the renewable energy source acts as a unit of "first choice". Where, the control parameter (λ in Fig. 6a,b) shows a dynamic variation in electricity cost which impacts directly on CAPP. It is also justified through simulation results (Figs. 3–6) that the customers are provided with the customized electricity prices based on load consumed. In response, the customers showing homogeneous energy consumption trends are not overcharged.

proposed pricing scheme based on dynamic trends of load demand, consumption behavior and pricing signal, $p^{act}_{PV_i}(t)$ is considered as a function of $p_{PV_i}(t)$ over time t and is calculated using the following expression and shown in Fig. 4:

$$p^{act}_{PV_i}(t) = \sum_{i=1}^{U}\sum_{t=1}^{T}(\overline{p_{PV_i}}(t) - \underline{p_{PV_i}}(t)\times f(i, \underline{p_{PV_i}}(t)) + \underline{p_{PV_i}}(t)) \tag{12}$$

$$\underline{p^{act}_{PV_i}}(t) \le p^{act}_{PV_i}(t) \le \overline{p^{act}_{PV_i}}(t) \tag{13}$$

Eq. (12) shows that the resultant output capacity is obtained in the form of a vector, which is integrated into the load scheduling control algorithm. It is also worth mentioning here that, each customer/user has a different renewable energy source with different variations, as shown in Fig. 4. Where, $\overline{p^{act}_{PV_i}}(t)$&$\underline{p^{act}_{PV_i}}(t)$ denote maximum and minimum limits on renewable power generation from photovoltaic source, and $f(.) = \mathbb{R}^+$ is a random function to produce positive real numbers with the normal distribution. Eq. (16) denotes the upper and lower limits on the total power from the renewable energy source. Based on Ausgrid solar home electricity data [53], the $\underline{p^{act}_{PV_i}}(t)$&$\overline{p^{act}_{PV_i}}(t)$ values are 0.5 and 1.4 $/KWh. Furthermore, it is understood that both uncertainty and variability may pose serious challenges to market operators in balancing generation and demand while obeying power system constraints. Generally, the solar and wind variability can be analyzed on single or multi-timescales [54]. Studies show that due to PV forecast uncertainty, the power dispatch cost may increase 3% and is 2% in the wind case [54]. These uncertainties can be significantly reduced by using advanced forecast algorithms [55], increase the dispatch frequency for quick scheduling intervals [56], and increasing the regulation reserves [57], respectively. Finally, the modified expression to calculate energy cost under renewable energy source integration can be expressed through Eqs. (10), (11), which gives the electricity cost when renewable energy or storage system is integrated to fulfill the energy demand. This work only considers RE integration, while the storage system is yet to be involved in future work to assess the performance under uncertainty. It is also worth noting here that, users have to pay the electricity bills in response to the energy consumed from the grid using the proposed mechanism. In contrast, the other mechanisms calculate bills without considering the benefits of other consumers. Eventually, this may disturb the end user's comfort who willingly participated in energy management programs. On the other hand, power system stability can be enhanced by reducing the peak load demand while meeting the end-user energy demand with available capacity. This objective can be achieved by rescheduling some loads in off-peak hours without creating rebound peaks. Otherwise, cost-sensitive customers having homogeneous load patterns might be charged high prices. To cater this problem, the load optimization problem can be designed in such a way to provide actual prices to all consumers while avoiding price discrimination along with power system stability in terms of a balanced supply–demand curve. The cost minimization objective function is written as [27]:

$$\mathbf{P1} = min \sum_{i=1}^{U}\sum_{t\in T}\Big(p_{g,i}(t)\times\varphi(t)\Big) \tag{14}$$

s. t: (Eqs. (1)– (7))

In **P1**, energy consumption cost is calculated using TOU pricing policy. While, the proposed method calculates the price on the basis of individual load profiles & pricing policy and TOU. For comparison purpose, the results obtained from Eq. (14) are used and the modified objective function **P2** is written as:

$$\mathbf{P2} = min \sum_{i=1}^{U} \sum_{t \in T} \left(p_{g,i}(t) \times c_{i,m}(t) \right) \tag{15}$$

$$p_{d_i}(t) = p_{g_i}(t) + p^{act}_{PV,i}(t) + p_{s,i}(t), \forall, t \in T, i \in U \tag{15a}$$

$$c_{tot_i}(t) = c_{ut}(t), \forall t \in T, i \in U \tag{15b}$$

$$p_{d_i^{un}}(t) = p_{d_i^{sch}}(t), \forall t \in T, i \in U \tag{15c}$$

$$\varphi_i^{hp}(t) > \varphi_i^{op}(t) > \varphi_i^{lp}(t), \forall t \in T, i \in U \tag{15d}$$

$$\overline{p_{d_i}}(t) < p_{d_i}(t) < \underline{p_{d_i}}(t), \forall t \in T, i \in U \tag{15e}$$

$$p_{d_i}(t) \leq \overline{p_{d_i}}(t), \forall t \in T, i \in U \tag{15f}$$

$$\underline{p^{act}_{PV_i}}(t) \leq p^{act}_{PV_i}(t) \leq \overline{p^{act}_{PV_i}}(t), \forall t \in T, i \in U \tag{15g}$$

$$\underline{p_{PV_i}}(t) \leq p_{PV_i}(t) \leq \overline{p_{PV_i}}(t), \forall t \in T, i \in U \tag{15h}$$

(Eqs. (1)– (11))

Eq. (15) gives the cost profiles of all $i \in U$ over time T. In this equation, it is mentioned that rather than using TOU pricing scheme, the proposed work uses the CAPP described in Eqs. (8)–(11). Eq. (14) shows the cost minimization objective function, Eq. (15a): refers that load demand must be fulfilled by energy taken from the grid, renewable and storage systems. Eq. (15b): shows that total energy consumption cost incurred in the proposed case must be equal to cost/revenue of the utility, as described in Eq. (16). Eq. (15c): depicts that unscheduled and scheduled load demand must be equal to keep the demand curve smooth. Eq. (15d): specifies the price tends for six time periods which are given by Al-Rubaye et al. [27] and adopted by the proposed work. Eq. (15e): gives the minimum and maximum limits on energy consumption over the given period. Eq. (15f) elucidates that load demand for any user must not exceed the maximum energy limit. Otherwise, the rebound peaks can be created due to overload conditions. Finally, Eqs: (15g), (15h) give upper and lower limits on power obtained from renewable sources. After considering all constraints, the optimization program provides the CAPP for all users, which later on is used to calculate the final electricity cost. Note that the solution returned by the optimization program contains the price profiles of each user along with an increase or decrease in tariff, through decision variable λ. From the results, it can be seen that the solution returned by the optimization program contains the price profiles of each user with the percentage increase or decrease in tariff and cost, which is heavily dependent on λ. To further validate the achievement of the proposed pricing policy, Lemma 4.1 is described below.

4.3.1. Price homogeneity

It can be formally proved that the CAPP for U users over t are homogeneous and non-discriminatory and customers unanimously accept these prices.

Lemma 4.1. *Let* $\varphi_{CAPP,i}(t) = \frac{\sum_{t \in T} \sum_{i \in U} p_{d,i}(t)\varphi(t)}{p^2_{d,i}(t)}$ *be the price profiles for all users* $iu \in U$ *in time slot* T*, and* $cost_{CAPP,i}(t)$ *(Eq. (8)) be the energy consumption cost for all users in response to CAPP. If the total energy consumption cost expected by the energy retailer is equal to the cost generated from all users* u *in accordance with the traditional method and the proposed CAPP, i.e.,* $(c_{CAPP,i}(t) = \mathbb{E}_{c,i}(t))$ *and* $(c_i(t) = \mathbb{E}_{c,i}(t))$*, then the price profiles obtained from CAPP are homogeneous*

Proof. let assume the price signal is received from the utility market, the energy consumption prices are calculated. Then based on the total cost for all users $i \in U$ over the given period T, the CAPP price profiles are obtained by taking the real-time consumption data from the community management system using the SG communication infrastructure. In a result, the energy consumption cost, i.e., $p_{d,i}(t)\varphi_{CAPP,i}(t)$ of all users U by using CAPP is obtained such that the condition $(c_{CAPP,i}(t) - \mathbb{E}_{c,i}(t)) = 0$ is satisfied without affecting other customers operating under the same distribution system operator (DSO). Furthermore, to have the utility operating in the safe region, i.e., the demand is fulfilled without the extra generation of peak power plants, load scheduling is performed. In this case, the scheduled load has been provided with new price signals which are calculated by using: (i) the total load demand $p_{d_i^{us}}$ kWh and cost in time T, (ii) the electricity price obtained from the energy retailer via the smart metering infrastructure, and (iii) the amount of rescheduled load $p_{d_u^{sc}}$ kWh. In a response, the total cost of all users must be equal to the cost of scheduled $c_{p_{d_i^{sch}}}(t)$ and unscheduled $c_{p_{d,i^{un}}}(t)$ load as given:

$$\sum_{i \in U} \sum_{t \in T} \mathbb{E}_{c,i}(t) = \left(c_{p^{us}_{d,i}}(t) + c_{p_{d,i^{sc}}} \right) \tag{16}$$

Algorithm 1: CAPP calculation using proposed algorithm.

```
1  Initialize parameters: p_{d_i} & electricity price;
2  minimize c_i(t);
3  for t=1:T do
4      for i=1:U do
5          if p_{d_i} ≤ p_{PV_i} + p_{s,i} then
6              use p_{PV_i} & p_{s,i} to meet p_{d_i}
7          else
8              solve P1, Eq. (14);
9              if min.P1 is found then
10                 save and display cost results;
11             else
12                 repeat step 9 until min(P1) found using φ(t);
13                 if min.P1 is found then
14                 solve P2, Eq. (15);
15                 calculate φ_{CAPP,i}(t) using (Σ_{t∈T} Σ_{i∈U} p_{d,i}(t)φ(t)) / p^2_{d,i}(t);
16                 if E_{cost,i}(t) = cost p_{d_i^{us}}(t) + cost p_{d_i^{sc}} then
17                     save and display results;
18                 else
19                     return to step 8;
20                 end
21             end
22         end
23     end
24 end
```

4.4. Proposed algorithm

In engineering and science, the deterministic & stochastic optimization algorithms have been widely used in the selection of best elements concerning some criterion, being given in the form of some limits and bounds. In its simplest form, an optimization problem consists of maximizing or minimizing some real function (i.e., based on a mathematical model) by systematically choosing inputs from within a given set and computing the value of a function. Generally, the deterministic algorithms find the stationary points in the decision variables and the optimal solution found could be local-optimum rather than the global-optimum. Moreover, with a rigorous mathematical formulation without stochastic elements, the results of a deterministic optimization process are well defined and replaceable. Finding a feasible sample for highly

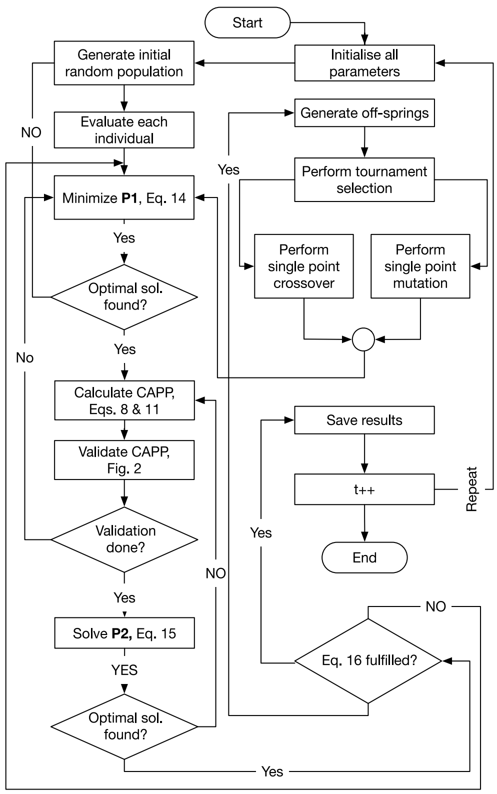


Fig. 5. Flowchart of the proposed algorithm.

constrained problems could be a challenging task. Although, suitable algorithms exist for accomplishing the tasks which are known as constraint satisfaction problems (CSP). Where a CSP can easily be solved by using heuristic optimization algorithms and can be considered a sort of optimization problem itself. That is why, this work has used the heuristic-based GA, which uses probabilistic transition rules, good in a noisy environment/data, can be used to solve mixed, discrete and continuous problems with single and multi-objectives. From the mathematical description of the set problem, it is obvious that the objective is to find the best solution. So, mathematical and heuristic algorithms due to its wide application are adopted to find the traditional optimum solution of the problem.

This work has used the GA to solve the optimization problem (Eqs. (14), (15)) by randomly creating a solution population of certain individuals in the form of binary bits (0 1 0 1 1 1). Where, each individual represents a solution (i.e., minimum cost) containing all kind of variables which are represented as chromosomes. Initially, the fitness value of a random population of 400 is calculated. This population size is considered to achieve the optimal solution with significant convergence. Once the fitness values have been assigned, the algorithm reproduces the copies of individuals to form the mating population. Reproduction may be done by a roulette wheel or tournament selection algorithms. In this work, a tournament selection mechanism is adopted, where two individuals are randomly chosen from the population with a random number $r = 0.75$. Single-point crossover with crossover probability $p_c = 0.9$ is used to reproduce new offspring, while 0.01 mutation probability p_m is selected. These values are chosen to tune control parameters of GA so as to get the convergence. After the selection, crossover and mutation, the new solutions is obtained and validated whether the fitness value fulfills the required criteria or not. Otherwise, the whole process repeats until the optimal solution is obtained. Algorithm 1 describes the working procedure of the proposed method. Initially, renewable & storage facilities serve as the first-choice to fulfill the load demand (step 6). If the load demand exceeds the available limit, then the p_g is used as a second source to provide the remaining load demand. However, it is also understood that due to variable load consumption patterns, the market price may fluctuate. Therefore, it plays a vital role in decreasing or increasing the end-user cost. To handle this uncertainty, the second source is optimally utilized and model the scheduling problems **P1** and **P2**, respectively. The **P2** is solved to fairly distribute the cost among all users. While the **P1** [27] is solved to compare the results with the proposed method. In addition, Fig. 5 describes the working steps of the proposed algorithm through the flowchart. The left side of the flowchart shows the steps involved in minimizing Eqs. (14) & (15), respectively. Initially, the Eq. (14) is minimized based on the initial random population of GA. However, the control moves further to minimize the Eq. (15) based on CAPP that is calculated and validated before min. Eq. (15) step. If the optimal solution is found, then Eq. (16) is first validated before saving and visualization. In the next step, the selection, crossover, and mutation operators are applied to again minimize Eqs. (14) & (15). This process repeats for t time slots.

5. Methodology & simulation results

Initially, the renewable energy source, which is preferred as the "primary source" of energy is used to fulfill the load demand. In case of load demand exceeds the $p_{PV}(t)$ limit, then $p_g(t)$ is used along with the renewable source. Now, there can be a probability of getting a higher price due to the variable load consumption trends, which are generally not known in advance. To handle this uncertainty, there is a need to obtain the optimal load patterns (steps 9–17 in Algorithm 1), which can further be used to achieve the minimum cost with possible avoidance of rebound peaks. Once the optimal results are obtained, the *Lemma* has to be validated. Otherwise, the algorithm would start from step 9, until the required conditions are satisfied. The cost results of load power extracted from the local grid have been shown in Fig. 6. This figure elucidates the actual cost results using the traditional and the proposed CAPP mechanism. Scheduled cost comparison using traditional and CAPP over a given period is shown in Fig. 6(a), while the unscheduled and scheduled comparison of price profiles is presented in Fig. 6(b). As a first observation, these cost curves seem irregular depicting dynamic load consumption behavior. Intuitively, the load consumption behaviors of all users/loads have similar patterns, i.e., each user has the same load pattern during a given time interval. However, these typical patterns originate from the fact that CAPPs are constructed in response to individualized load consumption patterns causing dynamic variations in unscheduled and scheduled cost curves (Regions-1&2, circles in Fig. 6c). Eventually, the homogeneous consumers receive reduced electricity bills without being overburdened due to the energy consumption of non-homogeneous consumers which is the objective of this paper. In contrast, the load consumption cost relies exclusively on conventional pricing techniques such as day-ahead or RTP which majorly depends on the "base-load" consumption [47]. Fig. 6c depicts unscheduled and scheduled cost profiles of i users over the 24 h time interval. The unscheduled cost curve seems to be higher during the periods of the high price. In contrast, the scheduled load curve depicts comparatively balanced behavior even due to the consideration of the load consumption capacity limit imposed to cope with rebound peaks. Otherwise, scheduling the load during the period of low prices may lead to the creation of rebound peaks and an unbalanced demand–supply profile. Although, such types of results may be found in real life as power generation fleets, exclusively rely on "base-load" technologies such as coal, fuel, and nuclear. Fig. 6d gives cost profiles of all users using traditional and proposed schemes. It can be clearly seen that each load has a different cost which is associated with respective load consumption trends. Similar trends can also be shown in all types of loads reflecting the impact of the proposed pricing scheme. Finally, Table 2 gives a summary of the obtained results in terms of increasing

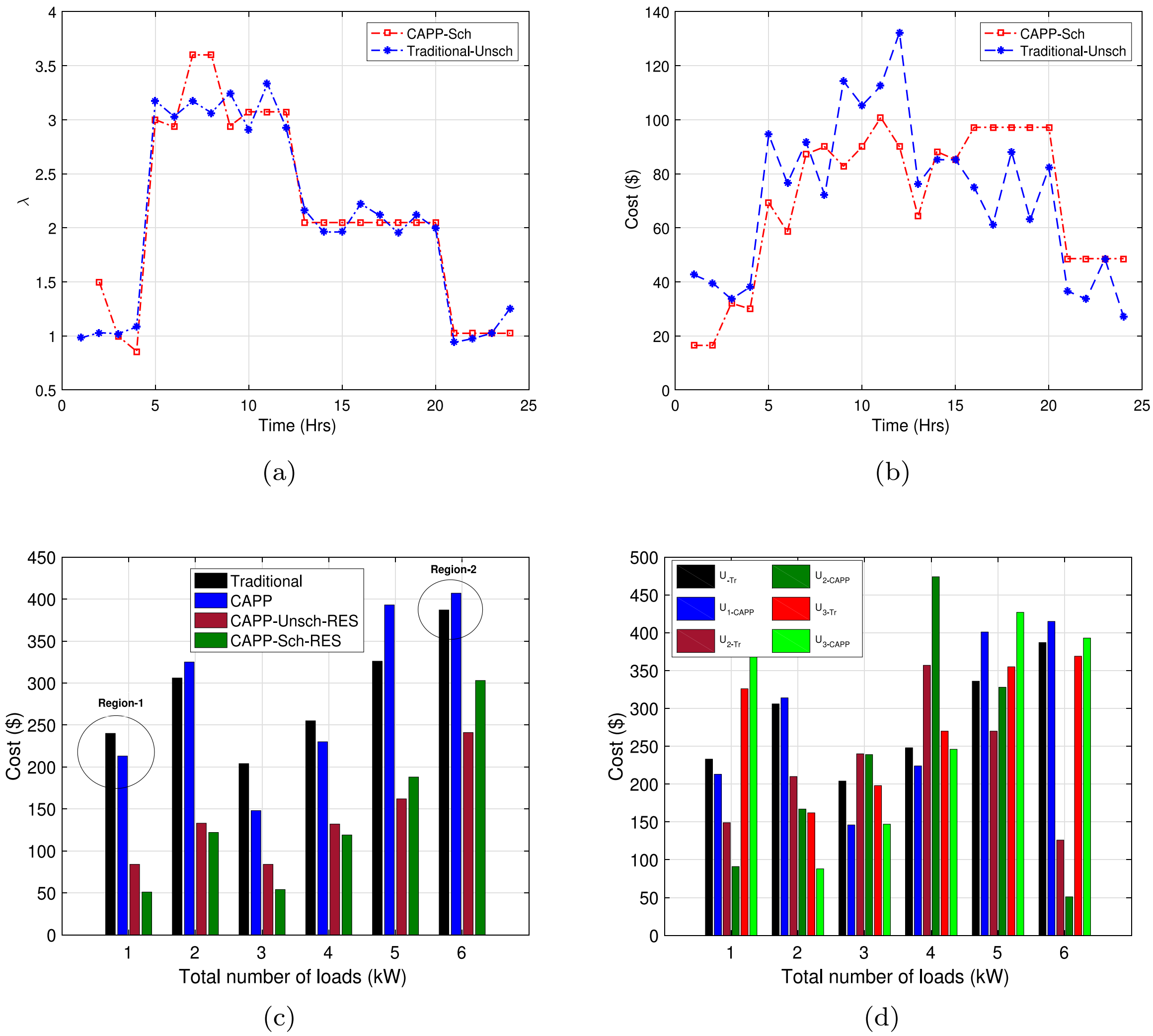


Fig. 6. A comparison of unscheduled and scheduled electricity cost over time t using traditional and CAPP. (a) The impact of the price factor in calculating the scheduled electricity cost incurred in response to the given price signal using traditional and proposed pricing mechanisms, (b) A comparison of unscheduled and scheduled electricity cost incurred in response to the given price signal using traditional and CAPP, (c) Scheduled electricity cost incurred in response to given price signal using traditional and proposed pricing mechanisms, (d) A comparison of energy consumption cost of all the users using traditional and proposed schemes. ($U-tr$ = User of traditional pricing scheme, U_{CAPP} = CAPP users)

Table 2
A cost comparison among traditional and proposed mechanisms over the period of 24 h against the total number of users and respective loads.

Pricing →	Traditional [48,49]	CAPP	% Impact	Traditional [48,49]	CAPP	% Impact	Traditional [48,49]	CAPP	% Impact
Loads↓	Users →								
	U_1	U_1		U_2	U_2		U_3	U_3	
1	233	207	−11.15	149	91	−38.92	326	380	+16.56
2	297	315	+6.06	204	164	−46.83	158	84	−16.45
3	198	143	−27.77	240	232	−3.33	198	139	−29.79
4	255	221	−13.33	357	479	+34.17	248	220	−11.29
5	336	407	+21.13	288	346	+20.13	355	441	+24.22
6	369	393	+6.50	126	51	−59.52	387	406	4.90
Total cost ($) →	**1688**	**1686**		**1364**	**1363**		**1672**	**1670**	

or decreasing in total cost and percentage. It is observed from the table that the total cost in traditional (TOU) and the proposed mechanisms remain the same, while the cost of individual loads in each home is different reflecting the impact of the proposed scheme. Fig. 7a further demonstrates the power profiles with the consideration of renewable energy source being used as a "first-choice". It can be clearly shown in the figure that the unscheduled demand profile is obtained from load data (Table 1), while the scheduled demand curve is obtained from the optimization program subject to respective constraints Eqs. (15a)–(15h). When the demand ratio swings over time due to dynamic load demand, the optimization program utilizes the full capacity of renewable energy resources, not just to incentivized users, but also to balance the load profiles. More interestingly, renewable energy source as presented in this paper has zero cost in the objective function what helps alleviating the need for a costlier generation. Fig. 7a also illustrates that from ($h_{16:00-24:00}$), the consumed power is comparatively higher than previous time slots. However, the respective cost seems

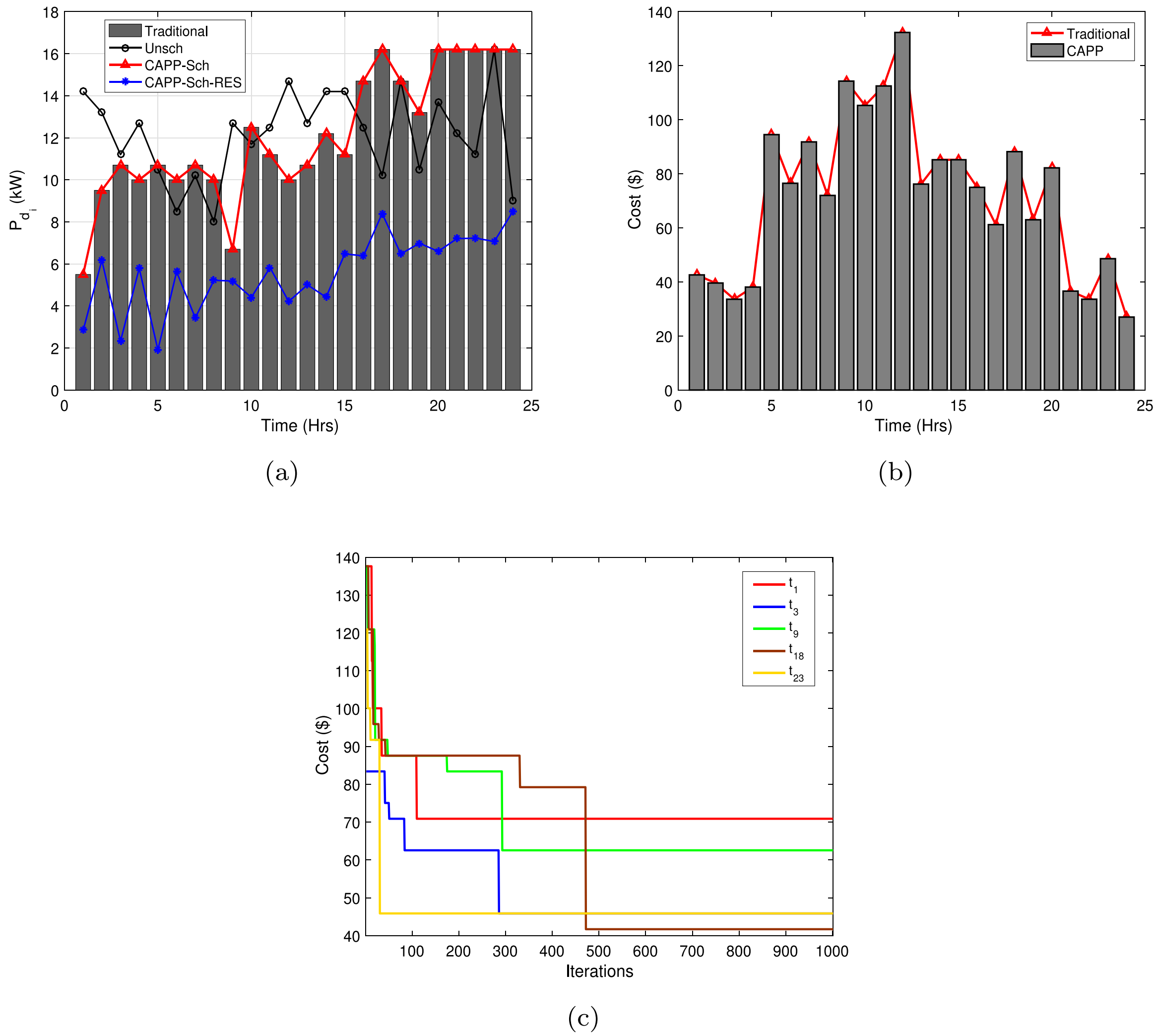


Fig. 7. A comparison of unscheduled and scheduled electricity cost and convergence over time t using traditional and CAPP. (a) Energy consumption profiles incurred in response to given price signal using traditional and CAPP, (b) A cost comparison using traditional and proposed pricing mechanisms over the 24 h time interval, (c) Convergence of the GA in finding the global optimal solution in terms of cost reduction over time slot t. It can be seen from the figure that in each iteration, the value of the electricity cost lies within maximum (approximately 138$) and minimum (approximately 42$) values. Because, in our system, the maximum energy consumption cost of all the loads cannot exceed the maximum value and never goes below the minimum value. It means, the fitness value must be within these limits, which is evidence that the fitness value is global. Furthermore, in each hour, the algorithm works to find the new optimal solution because the load demand, electricity price, and energy consumption trends are dynamic instead of fixed.

lower, which is due to the lower price as given in Fig. 2. Fig. 7b shows the associated cost of power consumption over 24 h time period. As it was demonstrated in Fig. 6a that electricity cost in response to traditional and proposed mechanisms show different trends. However, the total cost under the load consumption remains the same, which can be seen from Fig. 7b. It is thus bringing about extra benefits to all consumers who willingly participated in load management programs. Fig. 7c illustrates the convergence curve of the proposed algorithm. From the figure, it can be seen that for each hour, the convergence curve is different reflecting the dynamic behavior with respect to control parameters (i.e., cost, electricity price, load demand, consumption trends). This is because in each hour, the values of these control parameters are different and the algorithm has to find the optimal solution within given limits. Finally, Table 2 demonstrates the net cost of load consumed using both traditional and CAPP mechanisms, respectively. It can be visualized that the proposed mechanism does not affect utility's benefits, rather than on homogeneous consumers. It is also noted that the total cost of each user is approximately the same in both cases. It reflects that the proposed work deals with the fair cost distribution among all types of users based on the TOU pricing scheme.

6. Conclusion and future work

This work has proposed a novel electricity pricing policy "CAPP" based on DA-TOP signal and individualized load consumption patterns of the users. Unlike DA-TOU and RTP policies, the proposed scheme is designed to facilitate participating and non-participating customers to DR load management programs. For this purpose, an individualized load demand patterns and DA-TOU electricity pricing information from advanced metering infrastructure have been used. Then a distributed algorithm is designed to calculate the electricity price signal of each user based on his load demand electricity price information. This is a two-step process. In the first step, the energy consumption cost is calculated using the DA-TOU price signal. While the second step involves the calculation of CAPP based on individualized load demand data. For this purpose, the well-defined mathematical models and cost minimization objective functions are designed which later on solved by using GA. The validation of the proposed CAPP is done through analytical and simulation results. The results presented in both graphical and tabular forms show the advantage of the proposed scheme regarding cost reduction through load management and fair electricity price distribution among all users through individualized load demand patterns. Furthermore, the results also reveal that the GA is used in such a way to ensure optimal results. Because, instead of finding the optimal results for a specific time duration, the GA is implemented to find the results in each time interval. As the proposed CAPP is designed to provide fair electricity prices to all customers based on their demand without considering any limit imposed by the utility/retailer. However, the photovoltaic (PV) based renewable energy or electric vehicles (EVs) integration can help manage the end-user load demand without heavily relying upon grid energy only. This can not only help in alleviating the dependence on grid energy but also provide monetary benefits in terms of bill reduction. Therefore, future work will extend this model to integrate the standalone or grid-connected PV & hydrogen storage systems to manage the load demand with dynamic pricing policy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Compliance with ethical standards

This article does not contain any studies with human participants or animals performed by any of the authors.

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