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Game theoretic approach for energy scheduling in demand side management for smart grid applications

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The emergence of Game theory (GT) enabled with demand side management (DSM) has the applications in the field of smart grid applications. A mathematical method called game theory uses desirable rules to identify the circumstances under which all actors can win. Various agents can be used to optimize their gains. In terms of customer utility, demand response algorithms are categorized as agents in terms of customer utility. A centralized demand response (DR) scheduling algorithm that meets the varied energy consumption needs of a community can be difficult owing to the differences among residents. A non-cooperative DR-GT model is proposed to improve individual benefits in the energy consumption scheduling algorithm. The appliance information comprises different power levels to categorize the residents, which reduces the scheduling traffic between the residents and aggregator. There is a 23% reduction in the peak-to average ratio and increase in renewable energy usage by 13–25%, as better scheduling based on the flexibility of consumer loads and pricing schemes. Smart grid efficiency is improved by 23–30%, owing to reduced energy losses, fewer system imbalances, and lower wears on grid infrastructure.

Key words: game theoretic demand response algorithm, energy scheduling, energy consumption, load pricing schemes

1. Introduction

Demand-side management balances energy supply and demand in smart grids. Improving energy efficiency involves decreasing energy consumption and applying an understanding strategy of reducing overall demand for electricity while

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maintaining the amount of utility services [1]. Smart home users located in similar areas are the main players in the demand response (DR) programs. The strategy of independent decisions by home energy management systems (HEMS) has a positive impact and produces rebound peaks in power grids [2]. Game theoretic strategy is the collaboration between different entities in a smart grid to take advantage of cheaper electricity prices during off-peak hours with lower grid pricing intervals [3]. The intelligent devices react to DR programs managed by a controller, aimed at reducing power consumption and decreasing PAR and enhancing grid dependability [4]. This encourages consumers to comply with grid regulations and evens the load curve, thereby increasing the overall rate of energy utilization [5]. Because the electricity system can be reliably and economically optimized for base load demands, utility companies choose to run the system on this basis to maximize system efficiency [6]. Even if the base load is not the maximum generating capacity that a unit can provide, running beyond it is not economical and may compromise the stability of the entire power system [7].

1.1. Motivation

The aggregator collects appliance details, combines the load reduction ability of many residential users and sells them to markets [8], thus earning revenue for participating users. Therefore, they are typically situated between power grid utility operators and consumers. The aggregator gathers appliance data from residents, as well as their desired energy costs [9]. The load controls are used to curb demand based on price or other factors from the utility [10]. These controls could be integrated into home energy controllers and enable automated demand response programs to produce energy efficient reduction [11]. DR scheduling algorithms operate on an aggregator, which is a fundamental component of a DR structure. Therefore, they are Based on price signals, aggregators can facilitate real-time shifting of commercial and industrial loads to provide grid operators with demand-side management services [12].

Figure 1 illustrates the centralized DR design for a smart home neighborhood. Aggregators can offer a variety of supplementary services through optimization platforms, providing the system with more adaptability in integrating sources and appliances [13]. A DR system to manage the usage, storage, and transfer of battery-stored and renewable energy between homes and the grid, optimizing value for consumers and providing grid services as needed [14]. The proposed work examines the DR-GT in a smart grid, focusing energy distribution on the smart grid. Additionally, it outlines the typical ways in which energy is shared among residents. Subsequently, it examines how a variety of needs within a

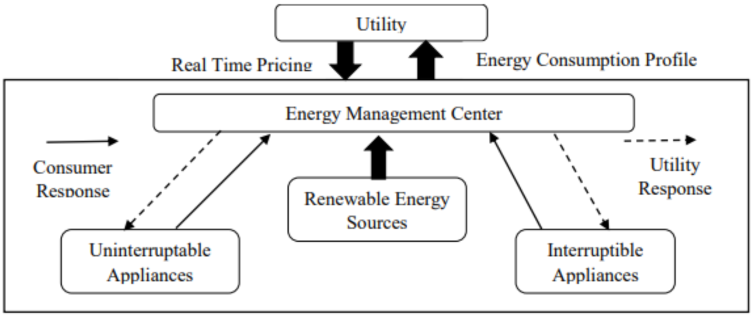

Figure 1: Centralized DR design

society is represented in a model. The contribution of the work is summarized into the following points

1. In the smart grid, a new discrete time dynamic game for scheduling energy storage is presented. A dynamic programming approach is used to obtain the best response problem's closed-form solution. The iterative procedure that follows swiftly approaches the Nash equilibrium.
2. DR-GT scheduling algorithm is proposed even in the worst-case situation, it is resilient to predicting errors. When compared to runs with precise predictions, the corresponding results show very minor variations in the PAR reduction outcomes and virtually no impact on the DR participants' financial gains.

1.2. Demand Response-Game Theoretic (DR-GT) scheduling

The DR-GT framework scheduling is illustrated in Figure 2. The primary component of the framework measures the diversity of users and their energy usage. The auxiliary component can optimally distribute energy by using a scheduling algorithm. The aggregator can assess the past appliance information and usage by each resident in the community. The process is defined as a workflow domain model that considers the smart grid architecture and is shared between the user and the utility. It displays an algorithm that plans load utilization by generating many customer tariff options so that the demand is kept to a minimum. This can be performed by a single user or several community members. The tariff is applied every hour, and the load can be rescheduled or shifted. Peak average Ratio, giving the proposed DR a distinctive feature. A specific case involving three residential customers and the algorithms correspond to user behavior without loss in comfort and the results were compared with existing algorithms.

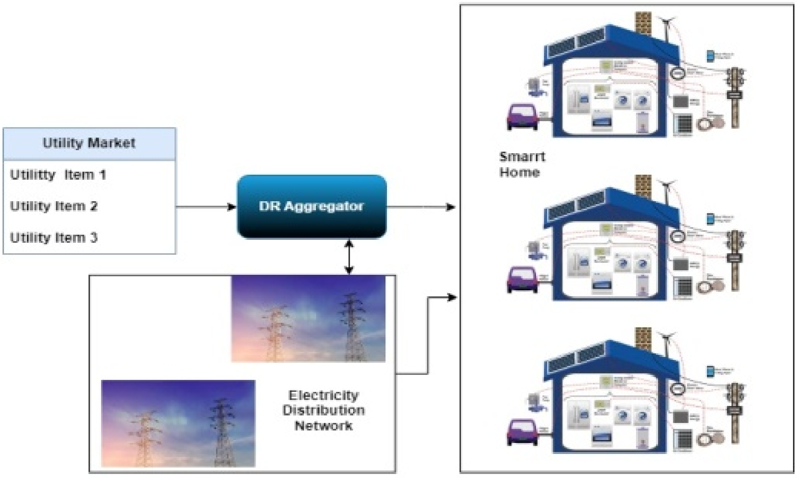

Figure 2: DR energy scheduler

Figure 2 depicts the complete architecture of the demand response scenario in the residential sector using a smart meter. The main goal is to develop a DR energy scheduler based on game theory that provides various optimal pricing options for each user from the utility provider. The system is mostly dependent on each user choosing their own winning approach, with individual participant selections coming in second order. In addition, the electric provider publicizes the demand period to lower, Thus, users will refrain from utilizing the DR programmed during peak hours. Imagine that, at approximately 10:00 am, power is inexpensive. Most consumers will turn on their appliances during this period, boosting demand and negating the goal of the DR program. The results from simulations using MATLAB and the computational simulation domain demonstrate how well customers' decision-making schemes work.

2. System model

The proposed DR-GT system is an embedded control system in which communication between residents and smart grid appliances ensures the quality of service. The utility function involves information on tariffs, environmental conditions, and energy demand estimation. The system utilizes knowledge of two technologies, DR and GT, for large-scale consumers and their scalability. Each user is designed to optimize the best energy scheduling for their appliance based on their payoff.

Players: $N = \{1, 2, 3, \ldots, N\}$ represents a set of users (households, industries, etc.).

Strategy: Each user selects an energy consumption schedule $x_i(t)$, where t represents time slots.

Utility Function (Cost Minimization): The cost function for each user depends on the total demand and dynamic electricity pricing.

2.1. Objective function

The cost function for each user is defined as:

$$C_i\left(x_i, x_{-i}\right) = \sum_{t=1}^{T} P_t . x_i(t), \tag{1}$$

where $x_i(t)$ is the energy consumption of user i at time t, P_t is the dynamic price depends on the total energy demand and x_{-i} is the consumption strategies of all other users.

2.2. Dynamic pricing model

The price per unit energy is often modeled as,

$$P_t = P_0 + \alpha \left(\sum_{i=1}^{N} x_i(t) \right), \tag{2}$$

in which P_0 is the base electricity price, α is a scaling factor related to demand-response elasticity.

2.3. Game Theoretic Equilibrium (Nash Equilibrium Condition)

Each user aims to minimize its own cost function while considering the influence of other users. The Nash Equilibrium (NE) is reached when no user can unilaterally change their strategy to achieve a lower cost:

$$x_i = \arg{}^{\min}_{x_i} C_i(x_i, x_{-i}) \tag{3}$$

for all $i \in N$, where x_i represents the optimal consumption strategy.

The main aim is to minimize the total cost by cooperative coalition

$${}^{\min}_{x_i} C\left(x_i, x_{-i}\right) = \sum_{t=1}^{T} P_t . X_S(t) \tag{4}$$

where $X_S(t) = \sum_{i \in S} x_i(t)$ is the total demand of the coalition.

The user-dominance game served as the foundation for the methodology. There are two categories for this. Utility side tariff generation is discussed in the first section. The user receives this information as a day-ahead schedule.

The user is responsible for adjusting the distribution in favor of low-tariff hours. The user's dominance game serves as the foundation for Methodology. There are two categories for it. The utility side tariff generation is covered in the first section. The utility produces different tariffs for different hours of the day, depending on the demand created by all users in the unit. The user receives this as a day-ahead schedule. The user is required to adjust the distribution in favor of low-tariff hours. More hours that meet the minimum rate are added to their schedule for the following day, and vice versa.

The proposed method uses an algorithm based on game theory that provides a distinct optimal price for every customer inside a utility. The control flow of the entire approach is shown in Figure 3 along with a flowchart.

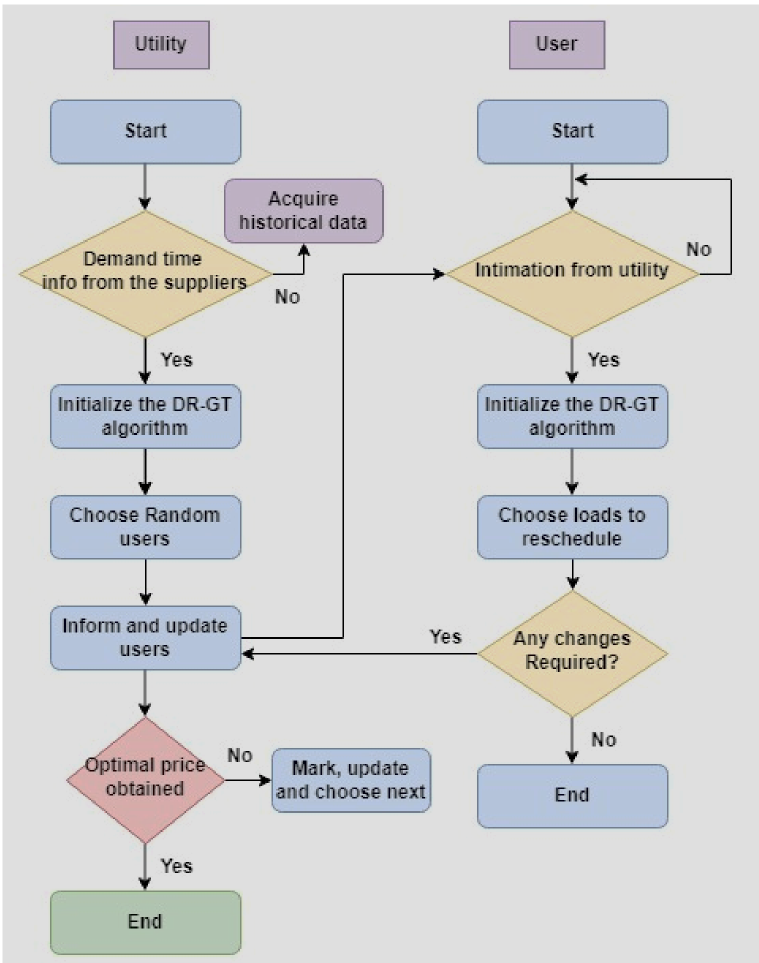

Figure 3: Flowchart of the model

3. Problem formulation with DR-GT algorithm

The DR-GT framework comprises a group of players denoted by $N = \{1, 2, 3, \ldots, N$, with N representing the overall number of players and the group of customers with a utility provider. N represents the total number of players who make up the group of consumers in a specific area with a utility provider. The player's strategy S relies on optimizing energy usage by scheduling the appliances.

Scheduling algorithm works on shifting the load to manage DR congestion and to develop steady state model. The pay is maximized during the optimal schedule and consecutively the PAR is minimized. The average power consumption is mathematically evaluated for each user, the cost function is denoted as

Minimize cost function $C_a^T \ L(f_{ah})$

$$\text{Subject to } \sum_{a \in A} X_{a,h} = L_{\text{Hourly}} < U_{\text{Hourly}} \,, \tag{5}$$

where C_a is the cost function.

Minimize the cost function $C^T \ L(f)$

where C_a – cost vector, L – Hourly load for 24 hours

$$\text{MinimizePAR} = \frac{\sum\limits_{n=1}^{N} \max(X_{\text{loadprofile-eachuser}})}{\sum\limits_{n=1}^{N} (X_{\text{loadprofile-eachuser}}) 1/T} \,. \tag{6}$$

The proposed algorithm was tested with a case study of three users in the same locality, and 15 appliances were embedded in the residential community. The utility provider is equipped with smart meters, controllers, and energy distribution networks.

3.1. Steps involved in DR-GT algorithm

The DR-GT algorithm is explained as follows

1. The cost vector C_a denotes the maximum demand of three users.
2. The PAR value is calculated for each user in each hour for the entire day energy consumption.
3. The optimal energy consumption scheduling vector is
$$X_{n,a} = \left[x_{n,a}^1, \ldots, x_{n,a}^H\right]. \tag{7}$$
4. The cumulative load of each user is $\sum_{a \in A} x_{n,a}^h$ where $h = 24$ hours.

5. The usage of each resident's load demand is calculated.
6. The total demand L is calculated by summing up total residents PAR value and the total demand is counted for the first four hours in a day.
7. The load values are arranged in ascending order and the load profile is created for case samples.
8. Rescheduling process is based on the matrix vectors and with time slot. The top-down methodology is applied to rescheduling process.
9. Total appliances are considered where the load is being shifted from hour to hour.

The load array vector is formed for shifting the load randomly for first 8 hours. The array vector is structured as 8×1 arrays of ones and zeros. Ones are represented to shift a load and zeros are represented as non-shiftable loads. The appliance array is updated, and the user's strategy is determined.

The players in a game are evaluated by the total tariff and their demand. The utility pay-off function of each player is $U_c^i = u_i(\text{strategy})$.

The players in the DR-GT strategy received the pay-off function once the scheduling is done and the cost minimization is achieved, so the Nash equilibrium state is obtained, and the maximum utility profit is the outcome of the game. The winning strategy is determined by comparing the scheduling vectors and is given as

$$U_i\left(s_i, s_{-i}\right) > U_i\left(s_i, s_{-i}^{-}\right), \ \forall s_i \in S_i . \tag{8}$$

Hence, utility function is proved to reach final Nash equilibrium stage.

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Hence, utility function is proved to reach final Nash equilibrium stage.

The demand hours are sorted from lowest to highest, updating the array according to the minimum hour. The ultimate winning strategy is achieved by determining the dominant vector and repeating the iteration process to obtain it.

Individual tariff of each resident is evaluated based on the dominant vector attained by DR-GT strategy. The demand hours are sorted from lowest to highest, updating the array according to the minimum hour. The ultimate winning strategy is achieved by determining the dominant vector and repeating the iteration process to obtain it. Individual tariff of each resident is evaluated based on the dominant vector attained by DR-GT strategy.

The mathematical model for the non-cooperative game is explained, and the optimal energy consumption scheduling is reached.

The strategic game model is,

$$\begin{gathered}\text{Game} = \left[\text{No. of users } n\left(S_i^n\right), \left(u_i\left(s_1, s_2, \ldots, s_n\right)\right)\right] \\ \min_{\forall n \in N} \sum_{n=1}^{N} \sum_{h}^{H} C_i^n f(h).\end{gathered} \tag{10}$$

The DR-GT game, characterized by power constraints, involves resident participation in selecting behavioral utility and obtaining power for each time slot. Each user has a unique scheduling strategy compared with the others.

Each player aims to maximize the utility function. The DR-GT game approach is used to derive analytical expressions to obtain the Nash equilibrium. A successful plan optimizes the personal payoff function. The player's action depends on the load profile with probability p_i to follow the strategy in each round t_i, there is no impact on the incentives obtained during play.

The strategy S_i of each player is given below, the game strategy exists for every round $t_i - 1 \geqslant 1$ and $h(t_i - 1) \in H$

$$\begin{cases} S_i\left(h\left(t_i - 1\right)\right)\left(c_i\right) = 1 & \text{if } \ p_i\left(t_i - 1\right) = 1 \vee t_i = 1, \\ S_i\left(h\left(t_i - 1\right)\right)\left(c_i\right) = S_i & \text{if } \ p_i = 0. \end{cases} \tag{11}$$

Each user's strategic activities are determined by the probability that they will cooperate, defend, and there is incentive-based in every round. Each player assessed the likelihood of the suggested game based on its cooperative strategy. In a game in which the consumer's proposed scheduling technique fails to reduce costs, the player advances to the next round without retribution.

$$S = \begin{bmatrix} b_0 & c_0 & d_0 \\ b_1 & c_1 & d_1 \\ b_2 & c_2 & d_2 \end{bmatrix}, \tag{12}$$

$$S_3 = \prod_{i=0}^{3} \left(\left(b_i c_i d_i\right) \vee \left(b_i + c_i + d_i = 1\right)\right), \tag{13}$$

where b_i, c_i, d_i are the user incentives.

3.2. Constraints

The constraints are expressed as follows.

$$R_{i_{\text{ind}}} = \left[\frac{\dfrac{H_{\max}(I_h)}{\sum_{h=1}^{H} \sum_{n=1}^{N} I_n^h}}{\text{No of user}N} \right], \tag{14}$$

where $E_i[h]$ is the per-unit value of the individual load profile of the consumers. Appliances are scheduled on demand based on the incentive strategy.

If a washing machine that follows a cyclic pattern and cannot be interrupted is considered shiftable, it is labeled as $g^n = 1$, while non-shiftable machines are labeled as $g^n = 2$.

$$\text{DemandResponse}[h] = \text{Shiftableappliances}[h] + \text{Non-shiftableappliances}[h]. \tag{15}$$

The demand response in hour is measured using the cumulative addition of shiftable and non-shiftable appliances. This equation shows that the overall electrical load at hour, the demand from shiftable appliances whose load operation is either scheduled or shifted to different time, and the demand from non-shiftable appliances whose load operation cannot be scheduled or shifted.

A maximum delay is determined in

$$\Delta g_{\max}^n = g^n - g, \tag{16}$$

$$f(h) = \Delta g_{\max}^n \left[\frac{\sum_{j=1}^{n} S_j}{K} \times W[h] + \sum_{t=0}^{t+1} S_j(h) \right]. \tag{17}$$

The value of K indicates that the total number of hours that the user is producing incentives.

3.3. Existence of Nash equilibrium

The convergence is achieved by all players (users) in an ongoing process involving repeated game slots. For example, the strategy derived from three users is denoted as $u(s_1, s_2, s_3)$ and repeated process until a convergence of inequality is reached is represented by Eq. (8) and Eq. (9) provides the payoff function for the final version of the game.

$$u_i(s) = p_i - \left(\frac{1 - c_i}{b_i - c_i} \right) + \min_{\forall n \in N} \sum_{n=1}^{N} \sum_{h}^{H} C_t^n f(h). \tag{18}$$

The payoff function $u_i(s)$ of the user i represents the winning strategy of the user by gaining the s_i maximum profit in every round. s_i in the game is the approach taken by everyone aside from the user at hand. The whole model demonstrates the novel gaming idea of finding the optimal strategy, with the winning strategy being modified through Nash equilibrium convergence.

4. Results and discussion

Mathematical computations were carried out to demonstrate how the recently introduced innovative approach can be effectively applied to demand response modeling for residential purposes, using data from three users and scheduling of 15 appliances per hour. The IEX standard tariff, which may be extended to numerous clients under utility providers, is used to determine time. A case study of an average workday in a flat area was created, together with estimates of tariff ranges and an analysis of energy usage

DR_GT Program used to create a load profile of three randomly selected users that were computed every four hours. The utility depends on the energy scheduling of a user. The following graph displays the load profiles of various household users. The computed tariff rate of utility in hour basis is given in Table 1, and Table 2 displays the appliance scheduling practices of a user, which is taken into consideration for 2 bedroom house as a vector in the suggested method for load shifting according to the PAR value. The values and graphs above depict the t users. The primary focus in the second stage is the user's dominant strategy generated by the utility according to the load profiles of three smart users. Tariff pricing scheme is followed when the consumers are charged based on their

Table 1: Random load power generated in per unit value

Smart home users	Hour 1	Hour 2	Hour 3	Hour 4
User 1	0.7094	0.6797	0.119	0.3404
User 2	0.7547	0.6551	0.4984	0.5853
User 3	0.2761	0.1626	0.9597	0.2238

Table 2: Tariff by utility (INR)

Domestic users	Hour 1	Hour 2	Hour 3	Hour 4
User 1	100	100	42	42
User 2	100	100	42	62
User 3	42	42	42	100

willingness to pay for scheduled power. The game Tables 3 presents the energy cost during with and without Game theory strategy. The inferred graph further illustrates that the cost is negligible for various types of consumers. Figure 4 shows that the approach is not being employed and that the cost is uneven over the hours. However, when the algorithm is put into practice, it is evident that the winning approach minimizes demand with a diversified load profile, while simultaneously lowering the costs for highly paid consumers.

Table 3: Without GT-DR strategy

Without game theory	Hour 1	Hour 2	Hour 3	Hour 4	Total cost (INR)
User 1	0	100	0	45	145
User 2	0	120	0	75	195
User 3	0	45	0	45	90

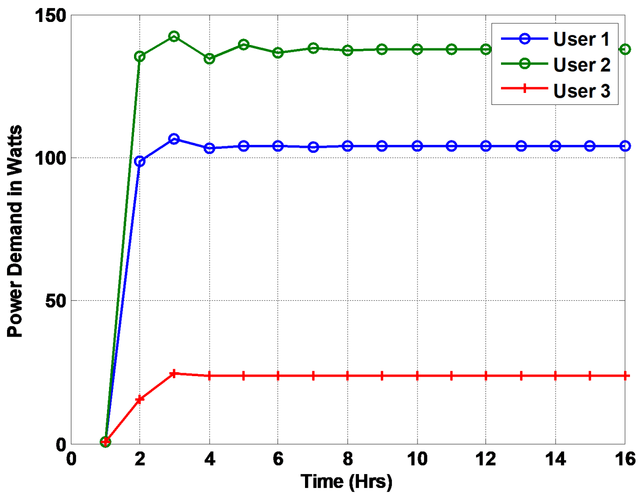

Figure 4: Load profile of three users calculated

Additionally, the performance was also assessed using the optimized DSM technique, a traditional Game Theory Energy Scheduler method [13]. The total number of customers considered in the system ranges from 3 to 20 users, each user is equipped with a smart meter to interact with the utility market. For demand side response scheduling, 15 household appliances are considered for every user, the evaluation is based on MATLAB simulations with system communication assumed to operate at a 2.4 GHz frequency band.

The findings explain why, compared to other game theory approaches, the GT-DR method's running time increased quickly when many users were considered. The proposed approach and the method considered were assessed using the GT-DR, as shown in Figures 5 and 6.

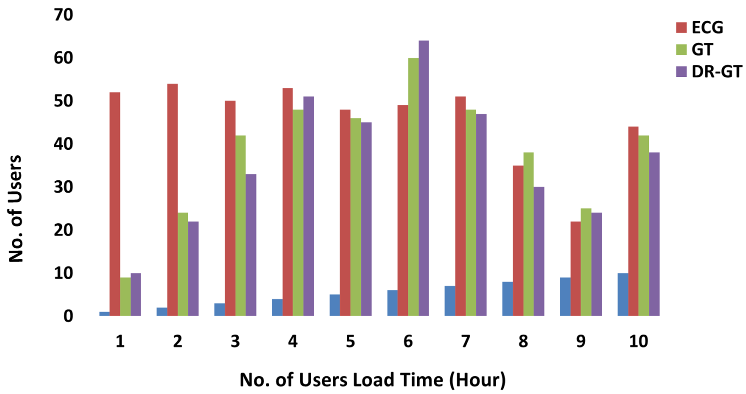

Figure 5: System running time – considering set of users

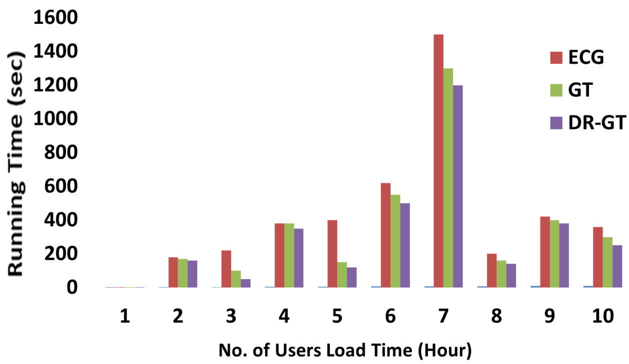

Figure 6: No of Iterations for various users

In comparison to the current algorithm, Figure 6 clearly shows how energy consumption games vary with the traditional algorithms. In addition, it refines the solution by tailoring it to each user. The scalability is good because of the lengthy assessment process that precedes it. The computed analysis of the GT-DR algorithm takes less time to complete than that of other traditional methods. Thus, it is validated more quickly. The system operating time for the 10 users is shown in Fig. 6 in a straightforward manner.

For 150 users, the system convergence of PAR and the utility market price for the GT-DR technique are shown in Figure 7, the PAR drops from 1.6 to 0.6. Furthermore, energy usage was variable and decreased significantly. It also shows how quickly the PAR converges throughout each algorithm round. It does not settle down and reaches a convergence point of 0.6 until after a few cycles.

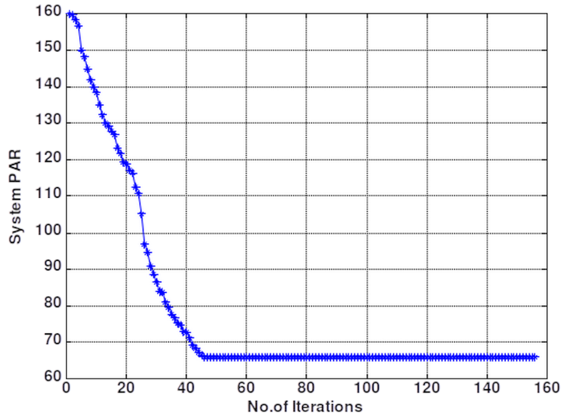

Figure 7: Convergence of System PAR

Thus, for each consumer, it now reaches stability and in equilibrium in the game theory stage and concludes that these consumers determine their ideal timetables. As before, the suggested algorithm has benefits for both users and the utility market. Energy efficiency lowers the need for new power plants capacity in power companies. The price function curve shows a significant decrease in customers' energy bills when they deduct from the load schedule. In case the consumer base grows, the ratio of iterations to users may be slightly reduced. The suggested approach is successful in attaining fast convergence rates and functions effectively with a high quantity of users. Reducing costs for users and minimizing PAR are the key factors in demand response modeling, resulting in an unbalanced load shape in the energy profile and requiring the creation of energy-conscious consumption habits. Energy savings cause electricity providers to develop fewer new power plants because their distribution and transmission capacities are significantly reduced. Based on the customers' own method of load schedule deduction, the price function curve shows a marginally lower energy cost. The suggested tactic shows rapid convergence rates and operates efficiently with numerous clients, which could be further examined. Decreasing user expenses and keeping PAR to a minimum are important factors in demand response modeling, as a rise in PAR can disrupt the load shape of the energy profile, which is essential. The GTFT method's performance is evaluated through a centralized game that is two-phase and top-down. The observation in Figure 7 and 8 confirms that the pricing parameter in the technique converges rapidly for both suppliers and users. They achieve balance and thereby validate the presence of demand response congestion. This plan indicates a greater rate of coming together. As a result, the best approach is to carefully manage energy usage at set times throughout the day without experiencing DR gridlock, rather than just altering energy consumption.

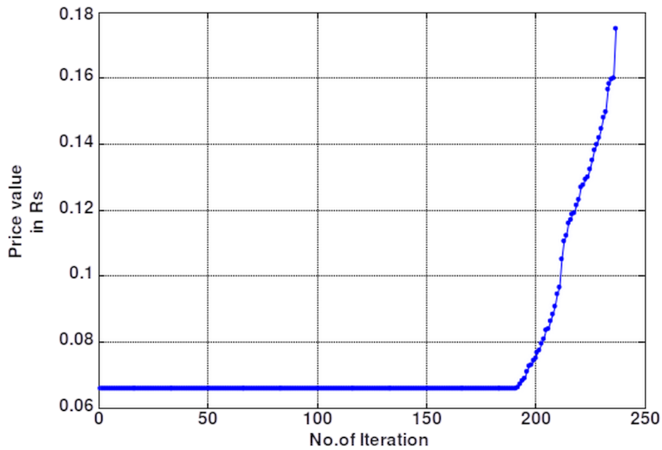

Figure 8: Convergence – supplier price

The analysis of the load curve shows that user 1 relies more on power demand from around 10 AM in the morning during the first iteration, with a balanced power demand compared to not using the strategy.

Figures show the comparison between users who implement the DR strategy and those who do not use the DR model for daily load scheduling development. Figures 9, 10, and 11 are the findings from the computational simulation and user

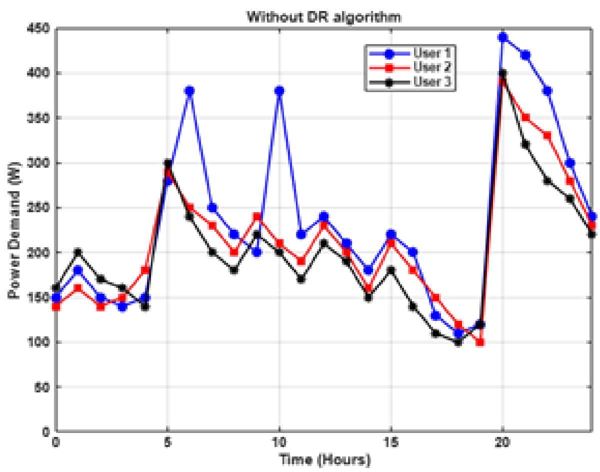

Figure 9: Load curves for user 1 with and without DR algorithm

feedback to demonstrate how the issue of DR congestion is addressed, revealing that there is some congestion when shifting load scheduling from off-peak to peak hours.

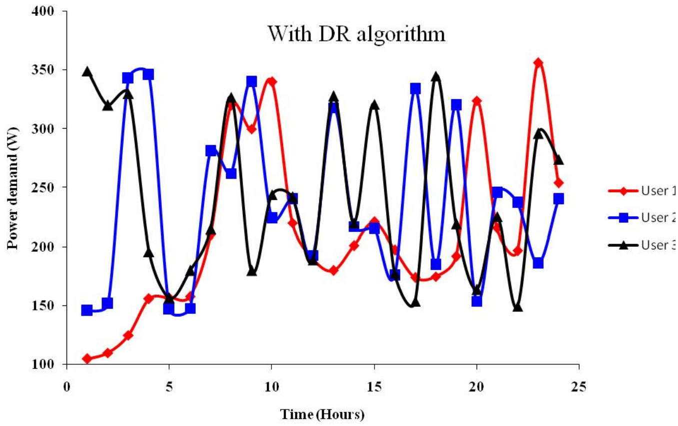

Figure 10: Load curves for users without DR algorithm

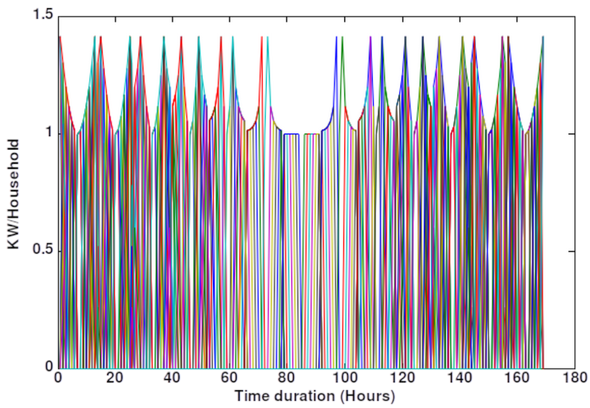

Figure 11: Analysis of users profile with DR strategy

The findings are compared with the technique in Figure 12, and during peak hours, the cost for one user is significantly lower. The curve is more linear in comparison with the other approaches; however, the other method produces a nonlinear curve. Reduced cost curves show that the significant reduction, because this system balances costs and reduces them significantly, various case studies have been examined in light of the average day schedule in which the algorithm operates in a smart grid setting. The outcomes obtained make it essential for the user to have a dual grasp of the utility and game strategy process.

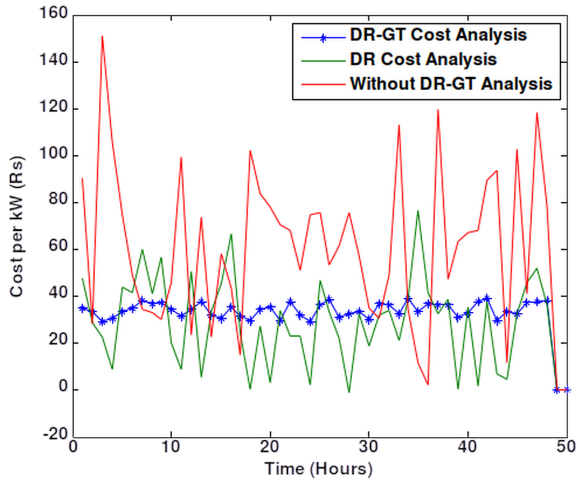

Figure 12: Cost analysis curve

Case 1: In this case study, the energy used by each user for a day was represented by the results of the aforementioned analysis. Depending on the PAR value, peak hours are changed to non-peak hours by creating individual tariffs.

Congestion results from moving loads to off-peak times. This confuses the issue with DR programs. The algorithm corrects and maintains by considering a scenario in which the winning technique is demonstrated. They maintain their top spot, and as a result, occupy the first order, during which the off-peak hours are more relaxed. The predicted outcomes for the three users are shown in Figure 13,

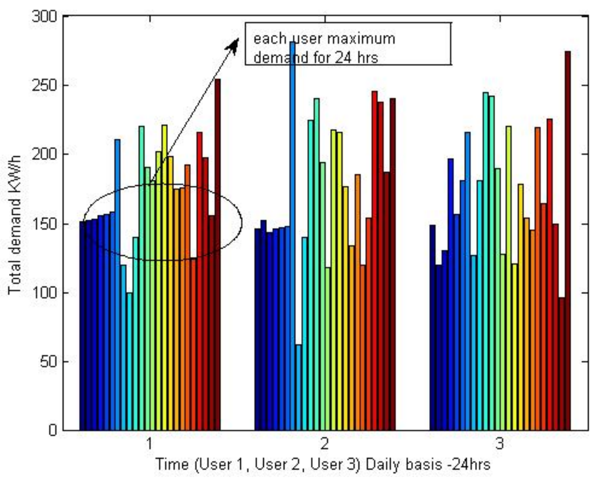

Figure 13: Energy consumed by 3 users for per day analysis

where the winning user creates an individual tariff and takes the top spot in an increasing order. This indicates a shift in demand and decrease in price. This concept is applicable to multi-user commodities.

Case 2: Based on the survey analysis presented in the Gujarat load survey report [2], the seasonal data analysis is examined. This instance is considered based on the climate in India, where appliance scheduling is based on end-user energy use. The algorithm model scenario for the load profile throughout India's summer and winter is shown in Figure 14.

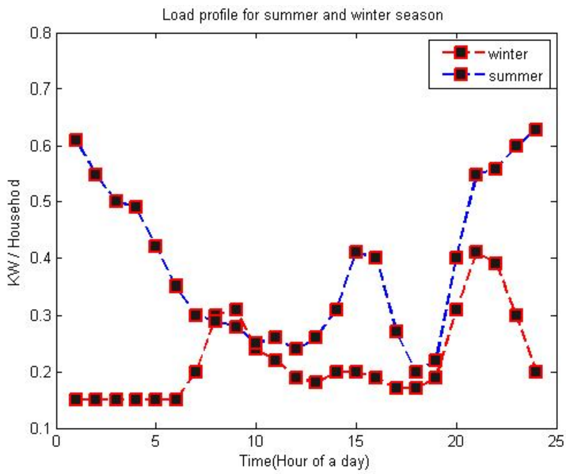

Figure 14: Load profile on summer and winter in India

The outcomes of the two simulations in Figures 15 and 16 show that demand-side management benefits both utilities and customers. In the case studies, the

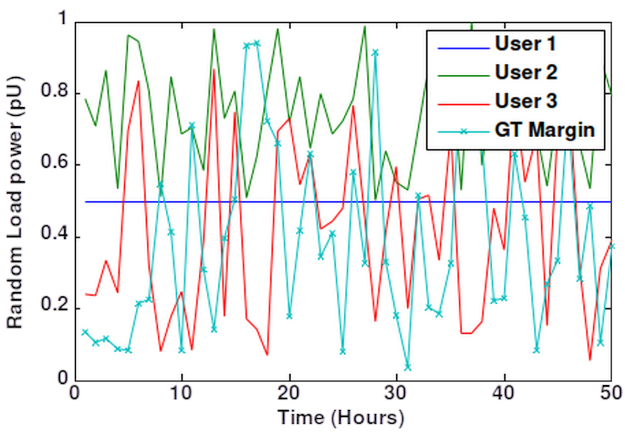

Figure 15: Seasonal profile (summer) based on DR strategy

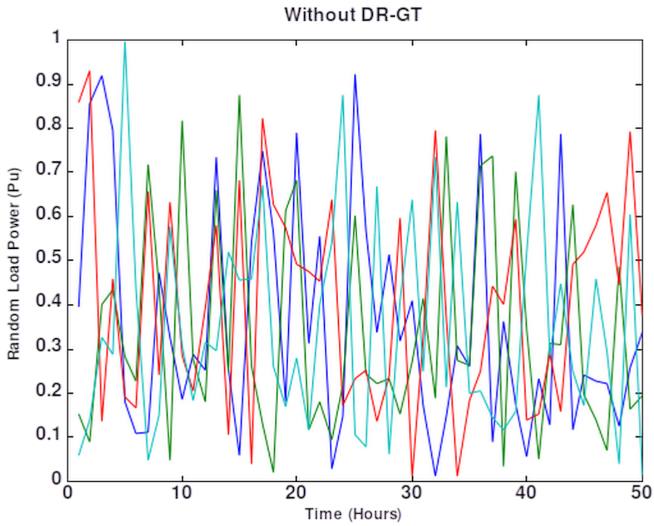

Figure 16: Seasonal profile (summer) based on random strategy

utility earned excellent savings in addition to the consumers, who achieved cost savings of 10%. They deal with situations in which various strategies are used to operate a smart grid. Controlling the load, pattern, and power consumption at each time slot requires further investigation. All the scenarios that are considered have computation times that are shorter than a whole day. When real-time load profile data from a location is taken into account, the dominating game strategy algorithm yields good outcomes and extending the algorithm's examination to a larger population of residential customers

5. Conclusions

In this study, a novel approach was implemented to establish an operational framework connecting the user and utility company to lower tariffs. This method takes into account shifts in peak load times by coordinating the use of appliances through a game theory approach between users, in addition to evaluating PAR in all customer interactions. Consequently, the new demand response algorithm displays dynamic behavior as it caters to multiple consumers within a community. The analysis of the findings was enhanced by using a distinct set of customers as a case study, resulting in a more solid foundation for the work due to the traditional assessment of the results. Furthermore, as a real-time dataset, simulations are run for this GT-DR system, taking into account various scenarios of the local climate. The simulation shows that by lowering the peak load consumption, the proposed technique provides users with significant savings.

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