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Stackelberg Game Theory Based Energy Management Systems in the Presence of Renewable Energy Sources

Akash Talwariya^a, Pushpendra Singh^a and Mohan Lal Kolhe^b

^aDepartment of Electrical Engineering, Institute of Engineering and Technology, JK Lakshmipat University, Jaipur, Rajasthan, India; ^bFaculty of Engineering and Science, University of Agder, Norway

ABSTRACT

The game theory concept has been adapted for energy management between energy producers and consumers in the presence of renewable energy sources (RES) and electric vehicles (EVs). The objective of the paper is to increase the penetration of renewable energy sources and EVs by the Stackelberg game theory model with real-time pricing. RES are the energy generation sources located near load centers to manage the demand of consumers. The primary objective of EV is transportation, but for managing the energy demand, EV participate in grid operations as a back up source of energy. EV are charged during off-peak hours and discharged to the grid during peak hours. Consumers benefited in terms of higher payoffs to supply energy during peak hours. To increase the payoffs, consumers can shift their appliance operation from high price duration to low price duration and create a new peak energy consumption. To maintain the balance between consumers and utility, an optimization tool is essential. The Stackelberg game theory model is a one leader and N followers' game, the leader first declares the energy price and the follower respond by selecting their best response for energy consumption. The leader can update its strategy again by considering the follower best response to obtain maximum benefits. The process to achieve the best response of the follower and leader is called the Stackelberg nash equilibrium. Objective of energy producers is to supply maximum energy through renewable energy sources and the use of EVs as storage units. The prime objective of consumers is to minimize energy tariff by scheduling the appliances.

KEYWORDS

Dissatisfaction function; Electric vehicles; Energy management center; Real-time pricing; Renewable energy sources; Stackelberg game theory model

1. INTRODUCTION

To perform day-to-day activities, consumers depend upon electric energy. Energy consumption is increasing and random in nature. It is essential for energy providers to manage the consumers demand by increasing generation capacity or by reducing the peak to average energy consumption ratio. A major part of the electric energy is generated from fossil fuels, but it has the worst environmental impact [1]. The suitable solution is provided by increasing the share of renewable energy sources (RES) in generation. RES are the green energy generation sources installed near load centers. Generation from RES is variable and depends upon weather parameters which affect the reliability of the RES. To improve the reliability of RES, a proper mechanism is required to store the energy and its supply during emergency [2,3]. The huge storage installation increases the cost of the system and needs another alternative. Electric vehicles (EVs) with vehicle to grid optimization can participate as storage units and should improve the reliability of RES without extra financial burden on energy producers [4]. Another method to maintain the demand of consumers by scheduling the appliances and providing incentives is called demand

response (DR). DR is a short duration energy consumption manipulation program that aims to reduce the difference between peak and normal hour energy consumption. Different DR methods are time of use, stepwise power tariff, real-time price, day-ahead price, etc. To maintain the balance among energy providers, RES, the EV charging–discharging model, consumers energy consumption, etc., an energy management center (EMC) is required [5,6].

Integration of RES with demand response gets the attention of researchers around the globe. In [7], the authors proposed the integration of RES with DR programs with a change in response to consumers in the availability and price of electricity over time. In [8], the authors manage the demand of large consumers with closed loop control strategies using information stemming from building and weather states by applying smart zoning. Smart zoning reduces energy consumption and increases the thermal comfort of consumers. The synchronous generators are control with high penetration of RES using interfaced converters in the power grid and maintain the grid stability for inherent characteristics of synchronous generators [9]. The random nature of electricity generation

due to environmental issues, imposes several technical challenges to power system operation as it is difficult to predict its output power. A two-stage stochastic programming problem simulates in real-time environment for load shedding at the consumer end [10].

In this paper, different appliances connected at the consumer end are categorized as interruptible and uninterruptible appliances based on their operation requirements [11]. If the energy consumption of appliances is schedulable and the energy level is variable they are called interruptible appliances, and if the consumption is neither schedulable nor variable they are called uninterruptible appliances [12,13].

The objective of the paper is to identify the interruptible appliances and manage their energy consumption within the available generation from RES and EVs. Categorized appliances, variable energy consumption patterns, random energy generation from RES and EVs random storage capacity make the system complex as shown in Figure 1, and an optimization tool is necessary. Game theory is useful for the optimum solution for integration of RES, EV and appliance management [14,15].

Game theory is a mathematical tool to optimize the conflict of interest problems, where each player tries to increase their payoffs. In this paper, consumers schedule their interruptible appliances from high to low price duration to increase payoffs and create a new peak. To estimate the resolution of the problem, the participation of energy providers is essential [16,17]. Stackelberg game theory model provides a suitable solution [18,19].

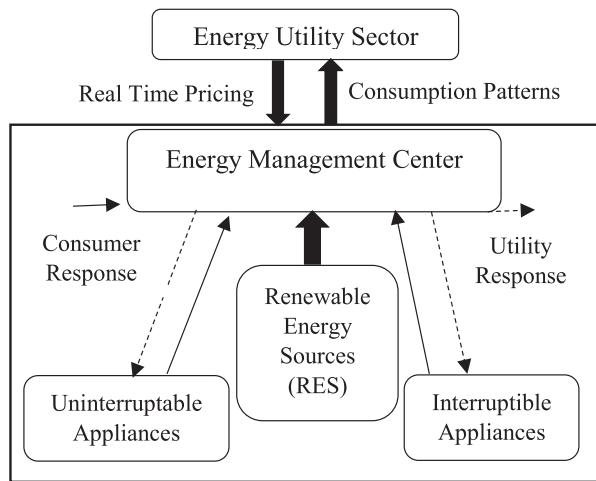


Figure 1: Process of energy trading between consumers and energy producers [4]

In Stackelberg game theory, two different groups of players participate. The first group of players are known as leaders and the second group of players are known as followers. In these games, the first leader provides a strategy and followers select the best response from their predefined set of rules. The players of Stackelberg game compete on quantity and leaders are sometimes the market leaders. In these games, the leader of the game must know the previous actions or the set of predefined rules [20,21]. The objective of the consumers is to minimize the energy tariff and the objective of utility is to manage the generation and supply energy all day. Stackelberg game theory is used for the optimization of the defined problem where energy producers select first and then consumers select their best response to get maximum benefits. In some cases, when utility select best response in the form of energy price, consumers shift their appliances to higher cost duration to lower cost duration and introduce a new peak. To negotiate the situation, energy producers update their best response and consumers need to proceed again from the initial stage. The process of selecting the best response is repeated again and again till optimization takes place in Stackelberg nash equilibrium [22–24]. In the Stackelberg game, leaders have the flexibility to change their response during the operation and followers follow the new response. The main Contributions are as follows:

1. To increase the penetration level of RES in the grid.
2. To enhance the reliability of RES by introducing EV as a backup storage.
3. A Stackelberg game theory model is designed and identifies the nash equilibrium between consumers and energy producers.
4. A dissatisfaction function is designed for different appliances and a Stackelberg nash equilibrium is obtained, which defines the coalitions of different players.
5. Comparative analysis of real-time pricing (RTP) and day-ahead pricing, simulation results show the effectiveness of the proposed model.

The rest of the paper is organized as follows: the introduction of the Stackelberg game theory model with assumption and mathematical modeling being provided in Section 2. Section 3 defines the Stackelberg game procedure to optimize nash equilibrium and algorithm of the Stackelberg game theory model. Section 4 contains the simulation results and shows the effectiveness of the proposed methodology, and Section 5 concludes the paper with outcomes and future scopes.

2. STACKELBERG GAME THEORY MODEL

The stackelberg game is a multiple players' strategic game of economics [25,26]. In this game the first leader firm selects its best response, and then the followers select their best response. The Stackelberg game is played between energy producers and consumers to maintain the peak to average energy consumption ratio and demand of consumers [27,28].

Some of the assumptions are considered before the implementation of the Stackelberg game theory model:

1. All consumers are equipped with different appliances which are categorized as interruptible such as washing machine (WM), air conditioner (AC), EV and vacuum cleaner, etc and uninterruptible appliances such as refrigerator, light, etc.
2. All consumers are connected to EMC for responsive demand management.
3. RES connected with EMC as the primary source of energy.
4. Energy producers circulate real-time price data and suitable energy management patterns to consumers.

A major part of electricity is generated from RES and connected with EMC [29]. The energy producer is managing the real-time price and energy consumption profile by scheduling of interruptible and uninterruptible appliances [30,31] as shown in Figure 1. The first energy producer selects a suitable strategy of energy pricing of consumption, and then consumers manage their consumption to optimize maximum benefits. If the peak to average energy consumption is not managed in the first attempt, the process repeats again and again till optimization of Stackelberg nash equilibrium. Energy tariff using the Stackelberg game theory model is designed mathematically by introducing the energy cost model for consumers and utilities.

2.1 Consumers Model

The objective of the consumers is to minimize their energy tariff. Energy tariff depends upon two factors: energy consumption cost and dissatisfaction function.

2.1.1 Energy Consumption Cost Model

The energy utility centers are financing huge amount on energy generation, distribution and transmission. The energy consumption payoff model for the consumers is based on two factors. First is appliance wattage, calculated based on dependency of consumers and second is the probability of the appliance to operate [32,33].

On the bases of energy consumption patterns, consumers are subdivided into $N_i = (n_1, n_2 \dots, n_i)$ categories and i denotes the consumer. Probability factor $p(n_i|n_{-i})$ is calculated by (1) where, $n_i \in N_i$ and $n_{-i} = (n_1, \dots, n_{i-1}, n_{i+1}, \dots, N_i)$ is the contribution of all consumers except the i th consumer.

$$p(n_i|n_{-i}) = \frac{p(n_{-i}, n_i)}{\sum p(n_i)} \quad (1)$$

The energy payoff function for the i th consumer for category n_i is given as $EPF_i(n_i)$ in (2):

$$EPF_i(n_i) = \sum_{n_i \in N_i} (p(n_i|n_{-i}, x_c) x_c(n_i)) p(n_i|n_{-i}) \quad (2)$$

where $x_c(n_i)$ denotes the wattage of constraint for category n_i of the consumer.

2.1.2 Dissatisfaction Function

The dissatisfaction function defines the satisfactory level of consumers for managing the demand based on patterns shared by EMC. To calculate the dissatisfaction function, calculate the median (K_i) of the average consumption for the i th consumer and compare the demand of the consumer with median consumption. If energy demand is more than K_i , the dissatisfaction function is negative and indicates the level of satisfaction of consumers with energy demand. The value of the negative dissatisfaction function decreases slower with the continuous energy demand of the appliances. If energy demand is less than K_i , the value of the dissatisfaction function is positive and increases faster if the demand reduces and connected appliances are dissatisfied with the available energy demand. If the energy demand is equal to K_i , the dissatisfaction function is zero and appliance preserves normal attitude during median energy demand. Dissatisfaction function conditions are calculated by (3)

$$\Phi_j(x_j) = e^{Y_j \left(1 - \frac{x_j}{K_j}\right)} - 1, \quad Y_j > 0 \quad (3)$$

where in (3), Y_j is the priority factor based on the energy consumption of appliances $j \forall (j \in J)$. A higher value of priority factor is based on maximum energy consumption. The objective of the consumer is to maximize the incentives provided by utility based on energy tariff denoted as $U_j(c, x_j)$ by (4)

$$U_j(c, x_j) = EPF_i(n_i) + \omega \cdot \Phi_j(x_j), \quad \omega > 0 \quad (4)$$

where in (4) ω denotes the satisfaction factor over duration. The total energy consumption pattern is subdivided into three sections, the first is peak energy consumption duration where consumption is higher compared

to average. The second is modest energy consumption where average energy is consumed and the third is low energy consumption where energy consumption is less compared to the average. If ω is high, the consumer is concerned about reducing the dissatisfaction factor.

The energy cost model is designed by selecting the best optimal strategy of consumers by considering the best approach of utility. The objective of the consumer is to minimize the consumption cost in (5)

$$\min U_j(c, x_j)$$

$$\min U_j(c, x_j) \quad (5)$$

A. s. t.

$$x_j^{\min} \leq x_j \leq x_j^{\max} \forall j \in J \quad (6)$$

2.2 Renewable Energy Source Cost

RES generate electricity in an indiscriminate way, and it is intricate to optimize the generation schedule. The RES energy cost model depends upon the capital investment and satisfaction cost factor [24]. The RES generation cost model is denoted by U_R in (7):

$$U_R = [R_R + C_R] \cdot X_R \quad (7)$$

where, R_R denotes the capital investment cost on renewable energy sources and energy management centers, C_R denotes energy bought charges from utility and X_R denoted as the satisfaction function parameter of RES.

2.3 EVs Energy Cost Model

The main objective of the EV is transportation, but the flexibility of energy discharging to the grid provides an opportunity for utility to use EV as a backup energy source. Consumers can supply extra amount of energy available in EV to the grid during peak hours. Consumers receive incentives in energy tariff to supply EV energy to the grid during peak hours. To enhance the benefits in terms of incentives, consumers supply more and more energy to the grid during peak hours. The situation increases the instability of the system and attention. To maintain the stability of the system, there is a need to bound the consumers to discharge of energy from EV to the grid [34]. Therefore, EVs discharging be the decreasing function. Let the total energy discharged by a consumer to the electric grid be Q_d , then the price model for the discharging function is calculated by (8)

$$U_{ev} = \sum_{t=1}^T I_t^d(Q_d) \quad (8)$$

where I_t^d is the incentive coefficient of discharging, mostly positive to provide benefits to the consumers. If the amount of energy supplied by consumers is introducing instability, utility adjusts the incentive coefficient and makes it negative. If the incentive coefficient is negative, consumers stop supplying energy to the grid as their energy charging cost is higher as compare to the discharging cost.

2.4 Utility Energy Tariff Model

The prime objective of the utility is to enhance the benefits by charging a suitable range of energy tariffs and maintain the peak to average energy consumption ratio. The conventional tariff structure is based on three factors: capital cost, per unit cost and installed capacity. These tariffs are constant throughout the day and do not depends on energy consumption patterns. The proposed Stackelberg game theory model provides an opportunity to update the strategy on the basis of the consumers' strategy. Another objective of the proposed model is to control the dissatisfaction cost function by appraising the strategy and getting maximum benefits for consumers and utilities by (9).

$$U_{utility} = \sum_{i=1}^I EPFi(n_i) + U_R - \sum_{j=1}^J \omega \cdot \Phi j(x_j) \quad (9)$$

where $EPFi(n_i)$ denotes the total profit gain by consumers by managing the demand. U_R denotes the cost at which utility bought energy from renewable energy sources. $\sum_{j=1}^J \omega \cdot \Phi j(x_j)$ is the dissatisfaction cost function that depends upon the satisfactory factor and reduces the overall tariff for consumers.

3. STACKELBERG GAME ANALYSIS

3.1 Game Procedure

The proposed Stackelberg game having one leader in the form of utility and N followers in the form of consumers are provided in the following sequence:

- A. *Utility company announces its strategy:* The Stackelberg game initiated when utility company announced its strategy including generation from renewable energy sources and conventional sources from the set $c = [c_1, c_2, \dots, c_N]$.

- B. *Consumer selects the best response:* When utility announces its strategy c , consumers I select the best response from their strategy set x_i , which is determined by solving (10).

$$x_i = \operatorname{argmin} U_j(c, x_j) \quad (10)$$

- C. *Utility Select Optimal Strategy Based on Best Response of Consumers:* Based on best response selected by the consumer, the utility will select the optimal strategy denoted as c^* , which is calculated by solving (11).

$$c^* = \operatorname{argmax} U_{\text{utility}} \quad (11)$$

- D. *Repeat A to C to obtain equilibrium:* Whenever utility selects the strategy, consumers have the react on it and provide the best response. When consumers and utility are satisfied with the response, Stackelberg nash equilibrium is obtained.

3.2 Stackelberg Nash Equilibrium

The Stackelberg nash equilibrium is obtained by maintaining a balance between consumer and utility [3,4]. Both kinds of players want to maximize their payoffs, consumers can get benefitted by applying the best strategy which minimizes the energy tariffs and utility gets benefitted by charging the maximum amount of tariff. Stackelberg gives a model where utility can update its strategy throughout the process. The nash equilibrium is obtained at a point where both kinds of players agree for coalitions. The Stackelberg nash equilibrium is denoted as (c^*, x^*) for the best strategy of consumers $x^* = [x_1^*, x_2^*, \dots, x_N^*]$ and c^* is denoted as the best response of utility are defined by (12)–(13):

$$(c^*, x^*) = \max_{(c, x)} U_{\text{utility}}(c, x^*) \quad (12)$$

s.t.

$$\min \min_x U_j(c, x_j) \forall j \in J \quad (13)$$

4. SIMULATION RESULTS

A renewable energy source of 500 kW is connected to the grid to supply a hundred domestic consumers. Domestic consumers are equipped with different appliances such as air conditioners, WMs, refrigerators, lights, fans and dishwashers (DWs). Based on the appliances are categorized into two categories, uninterruptible appliance whose energy consumption duration and schedule are not variable and interruptible appliances whose duration of conduction and schedule both are variable [35]. These appliances basically provide comfort to the consumer

Table 1: Characteristics of interruptible appliances

	AC	DW	EV	WM
Priority factor of Appliance	3.5	4	5	4.5
Energy consumption (kWh)	2–3	3–5	1.5	1–3
Duration of conduction (h)	8–10	2	2	5–6

Table 2: Characteristics of uninterruptible appliances

	RF	L1	L2
Priority factor of appliance	1.5	2	2.5
Energy consumption (kWh)	1.5–3	0.5–1	0.5–1
Duration of conduction (h)	24	8–10	8–10

and movable in the schedule to enhance the payoffs such as in air conditioners, DWs, etc. A small microgrid containing hundred domestic consumers are taken into consideration for the implementation of the proposed approach. An assumption is taken that each consumer is equipped with four appliances from the group of interruptible appliances which are AC, DW, WM and EVs, and three uninterruptible appliances refrigerator (RF) and two lights denoted as L1 and L2. Characteristics of interruptible and uninterruptible appliances are given in Tables 1 and 2, respectively. The appliance characteristics indicate power consumption, duration of conduction and probability of appliances [36,37].

The priority factor of the appliance is varied from 1.5 to 5, and the minimum range indicates the highest priority of appliance and the maximum indicates the lowest priority of appliance to be conducted in peak hour duration. The second constraint is time duration divided into three categories, off peak duration from 12:00 pm to 07:00 am with a satisfaction factor of 0.18, for mid peak duration from 10:00 am to 05:00 pm and 10:00 pm to 11:00 pm with a satisfaction factor of 0.1 and during peak duration from 08:00 am to 10:00 am and 06:00 pm to 10:00 pm with a satisfaction factor of 0.07 [14]. Figure 2 shows the average energy consumption of connected consumers

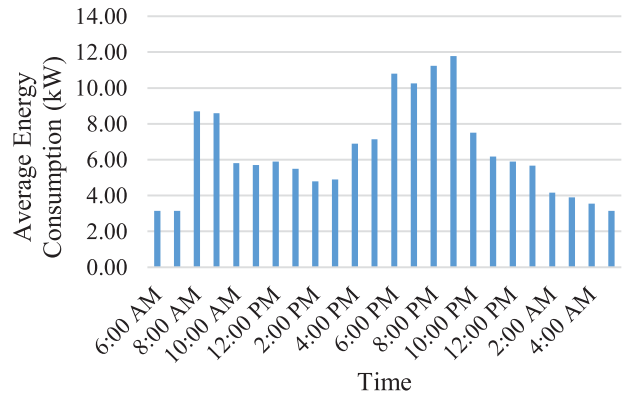


Figure 2: Average energy consumption of a hundred consumers.

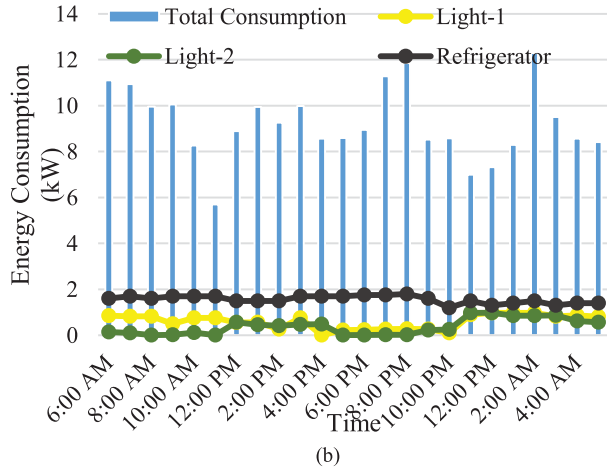
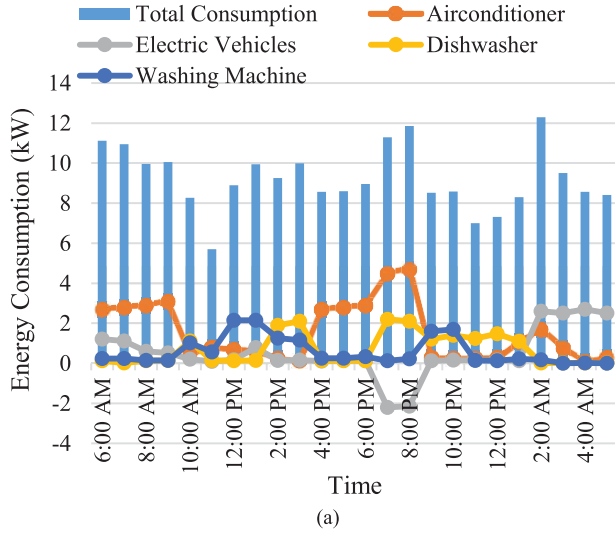


Figure 3: Average energy consumption compared with total consumption: (a) interruptible appliances and (b) uninterruptible appliances

in a microgrid before the implementation of demand response management through Stackelberg game theory. Total average energy consumption of hundred consumers in a microgrid is 154.29 kW, the average is 6.43 kW/h, maximum and minimum energy consumption is 11.78 and 3.15 kW, respectively.

Total energy consumption of interruptible appliances is 79.47 kW, average consumption is 3.311 kW/h, maximum consumption is 4.875 kW and minimum energy consumption is 1.615 kW. Figure 3(b) shows the energy consumption of uninterruptible appliances and compares it with total energy consumption. Total energy consumed by uninterruptible appliances are 60.875 kW, average is 2.53 kw/h, maximum consumption is 3.37 kW and minimum consumption is 1.55 kW.

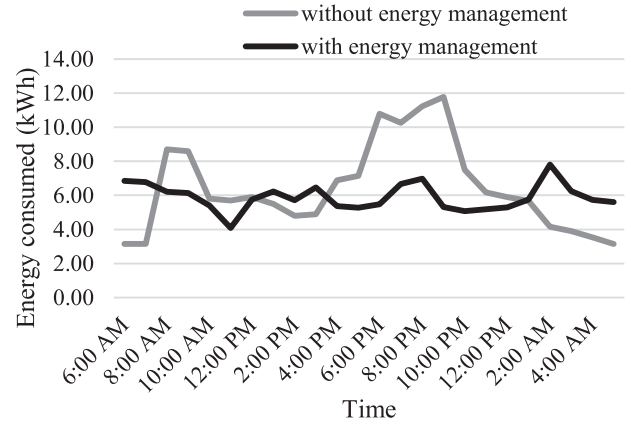


Figure 4: Average energy consumption with and without energy management

The primary objective of the energy management center through Stackelberg game theory is to maintain the peak to average energy consumption ratio. As shown in Figure 4 energy consumption with the proposed methodology is more linear and less peak to average energy consumption ratio. Energy consumption during peak hours is reduced from 11.78 to 7.8 kW and off peak load energy consumption is increased from 3.15 to 4.08 kW using the proposed methodology. Total energy consumption is also reduced from 154.29 to 141.38 kW, and the average energy consumption reduced from 6.43 to 5.89 kWh providing benefits to consumers and utility.

Energy consumption price is schedule day ahead by utility first, and as per the strategy selected by consumers, utility updates its strategy in the Stackelberg game theory model. The RTM model provides the energy price of the hour 15 min ahead. Day-ahead pricing is the tariff strategy provided day ahead to consumers for energy management. In this paper, after scheduling the appliances' energy tariff is calculated for RTP and day-ahead pricing. The data for real-time and day-ahead pricing are taken from the commonwealth Edison (ComEd) company website for the date 11 September 2019 [30]. Figure 5 shows the real-time and day-ahead price and represents that real-time price is less as compared to day-ahead price and provides benefits to consumers. Results show that the total energy price reduced from 259.35 ¢ to 249.91 ¢ when using RTP instead of the day-ahead price. The average hourly price reduced from 10.80 ¢/hour to 10.37¢/hour.

Different energy appliances consume energy in different fashions and the real-time energy pricing of different appliances are shown in Figure 6. Energy consumption cost depends on appliance operation and the priority

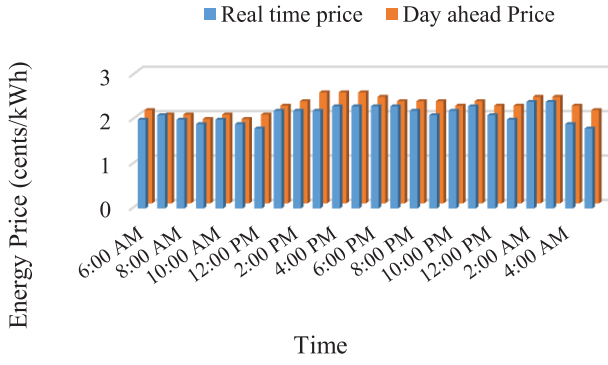


Figure 5: Hourly energy consumption price (Comed)

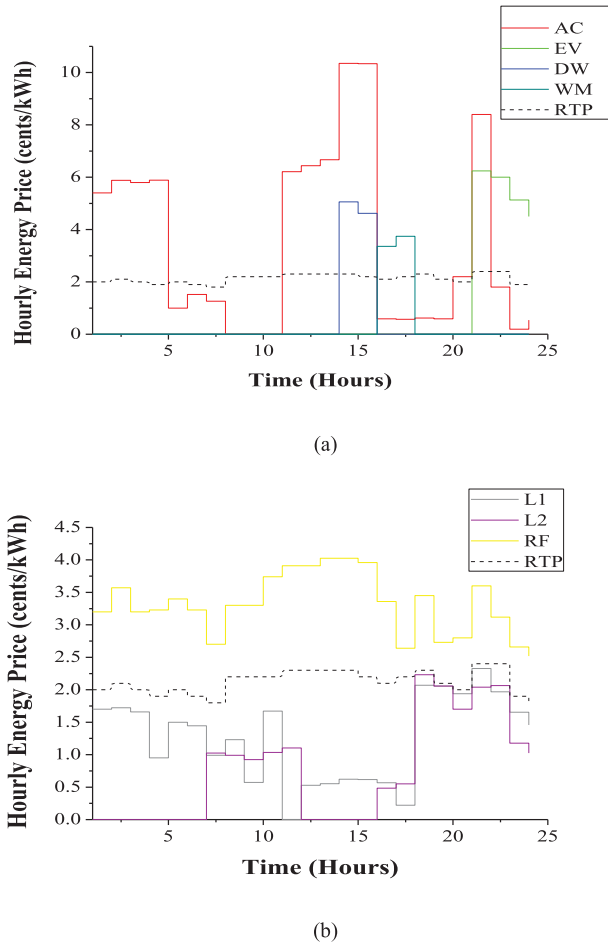


Figure 6: Hourly energy price for residential consumers: (a) interruptible appliances and (b) uninterruptible appliances

factor denoted in Tables 1 and 2. The priority factor of EV is the highest and the dissatisfaction function is an exponential function that represents low priority for the highest priority function. EV does not consume energy during peak hours and is shown in Figure 6(a). DW and WM priority factor are also high as compared to AC and consume less energy during peak hours. The

air-conditioned priority factor is the lowest in interruptible appliances and consumes a huge amount of energy throughout the day. The priority factor for AC is considered low by considering the geographical condition of India and the dissatisfaction factor. Consumers are spending more money on AC for their comfort. Figure 6(b) represents the uninterruptible appliances' real-time price and indicates the lowest priority for refrigerator and consume maximum energy and energy price is highest in uninterruptible appliances. The L1 priority factor is lower than L2 and allows L1 to consume more energy compared to L2.

5. CONCLUSION

Energy consumption management is essential to fulfill the demand of consumers with RES. The Stackelberg game theory model is used for integration of RES, appliance scheduling of interruptible and uninterruptible appliances through the energy management center. An algorithm of Stackelberg game theory is designed using mathematical modeling to maintain the win-win situation between consumers and utility. The objective of consumers is to minimize the energy tariff by scheduling different appliances, and the objective of utility is to reduce the peak to average energy consumption ratio. The proposed methodology has been implemented in a hundred domestic consumers. The results show the reduction in the peak to average energy consumption ratio and reduction in the energy tariff for consumers. The energy tariff of RTP is also compared with day-ahead pricing and provide better results. In the demand side management techniques, participating customers may have different preferences for shifting the operation of the selected loads. If there is a relatively more number of customers who are participating in demand-side management, then there is a possibility that the considered off-peak period can become the peak period. In such a type of scenario, relatively more time will be required to converge, and a further modification in the algorithm is needed with convergence as well as the rebound effect.

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AUTHORS



Akash Talwariya received the BTech in Electrical Engineering, MTech in Power System from Rajasthan Technical University, Kota, Rajasthan, India, in 2011 and 2015, respectively. Currently he is pursuing PhD degree in Electrical Engineering from JK Lakshmipat University, Jaipur, Rajasthan, India. He joined the Department of Electrical Engineering at JECRC University, Jaipur, Rajasthan, India. His current research interest includes smart grids, game theory, demand-side management and future network architectures. He published research papers in SCI and SCOPUS journals and conference proceedings. He was a member of the Institute of Scientific Research and Development. He was awarded Excellence in Academics by Institute of Technical and Scientific Research.

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Corresponding author. Email: akash.talwariya@gmail.com

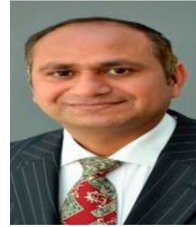


Pushpendra Singh received the MTech in Power System and PhD in Electrical Engineering from Malviya National Institute of Technology (MNIT) Jaipur, Rajasthan, India. He is currently Associate Professor, Department of Electrical Engineering, JK Lakshmipat University, Jaipur, Rajasthan, India. He is the member of The Institute of Engineers, India. His research experience includes power

of Engineers, India. His research experience includes power

system restructuring, power quality, integration of DERs, demand-side management, power system stability, smart grid, distributed generators, climate change mitigation, etc.

Email: pushpendrasingh@jklu.edu.in



Mohan Kolhe received the bachelor's degree in Electrical Engineering from MA College of Technology Bhopal, Bhopal University, India, in 1989, and the Master's and Doctorate degrees in Energy Engineering from the Indian Institute of Technology-Delhi, New Delhi, India, in 1991 and 2000, respectively. He was a

member of the Government of South Australia's first renewable energy board (2009–2011) and actively contributed to developing renewable energy policies for South Australia. He was the Research Director (Renewable Energy) at the University of Jyväskylä, Finland, where he developed the facilities for renewable electrolytic hydrogen production, fuel cell-powered small cars, and courses for the master's program in renewable energy. In January 2007, he joined the College of Art, Science and Engineering, University of Dundee, Dundee, UK, as a faculty in renewable energy. Currently, he is working as Professor Department of Electrical Power Engineering, University of Agder, Norway. His current research interests include solar energy, fuel cell technologies, integration of renewable energy systems and energy economics.

Email: mohan.l.kolhe@uia.no