Journal of Sustainable Development of Energy, Water and Environment Systems

http://www.sdewes.org/jsdewes

Year 2020, Volume 8, Issue 3, pp 547-560

Intelligent Algorithm for Efficient Use of Energy Using Tackling the Load Uncertainty Method in Smart Grid

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Cite as: Khan, S. N., Intelligent Algorithm for Efficient Use of Energy Using Tackling the Load Uncertainty Method in Smart Grid, J. sustain. dev. energy water environ. syst., 8(3), pp 547-560, 2020,
DOI: https://doi.org/10.13044/j.sdewes.d7.0308

ABSTRACT

In this paper, i am developing a unique optimization based real time inland load management algorithm that takes into account load ambiguity in order to minimize the energy payment for each residential user, as well as reduce the peak to average ratio to overcome the drawbacks in the stability of electrical grid. By categorizing the all residential load in different classes, i.e. must run, interruptible and uninterruptible appliances, i used the real time pricing scheme for load management. However, real time pricing creates the peak profiles when the energy demand is too high, that's why i used the combination of real time pricing and inclining blocks rates model to improve the grid stability by reducing the peak to average ratio. A simulation results show that the proposed algorithm efficiently and effectively reduced the overall residential energy cost as well as peak to average ratio of our model for data provided.

KEYWORDS

Demand side management, Peak to average ratio, Energy cost, User comfort, Smart grid.

INTRODUCTION

The advanced technologies in communication, distributed generation, cyber security, and advanced metering infrastructure of smart grid enhance the efficiency, reliability, and flexibility of the power grid [1]. Due to preset fashion and behaviour of suppliers and consumers, smart grid improves the competence, reliability, economics and sustainability of the fabrication and distribution of electricity. Due to different protocols, self remedial and intelligent communication sharing transportation, smart grid provides different techniques and algorithms to use energy more sensibly and effectively at demand side [2]. Demand Side Management (DSM) encourage and assist the user to shift their load from peak time slots (where the demand of energy is too high) to off peak time slots (where the demand of energy is low) [3]. Recently, one of the crucial DSM activities is Demand Response (DR), it is presumed that DR is a subset of DSM in broader aspect. DR is defined as the tariffs or program established to influence the end users to reshape their energy consumption profile in response to electricity price [4]. Among different techniques, i.e. direct load control and smart metering encourage the user to shift their load [5]. Demand management algorithm using the net metering techniques in which customer are encouraged to install renewable sources at demand side and extra generation will be sent back to utility [6]. Real time demand response, also a model used in when real time data is provided by the customer to utility [7]. Game theoretic model, incentive based energy consumption algorithm, autonomous three layered structure model and Vickrey Clarke Groove Mechanism are the techniques of DSM that manage the consumption in different prospectus [8]. Game theoretic method is also method implemented to get discussed results [9]. Some heuristic policies are also introduced to manage the energy consumption when it exceeds the threshold point [10]. Some techniques minimize the energy cost while some reduce the Peak to Average Ratio (*PAR*) but in limited amount. Table 1 gives all the described information about heuristic techniques used to attain the mentioned purpose. Limitation of each technique is mentioned briefly in referenced table. After visualizing limitation of all techniques we planned the algorithm that reduce the overall energy payment for user and reduce *PAR* in greater amount. Our algorithm will consider the user comfort as well. A new model of Real Time Pricing (RTP) will be introduced in coming sections in which a user will have to sufficient time to schedule the operation of household load.

Table 1. Heuristic techniques

Techniques names	Aims and objectives	Descriptions	Limitations
Hybrid technique [Genetic Algorithm (GA) and Particles Swarm Optimization (PSO)] [11]	Minimization of cost and *PAR*	Distributed energy resources and energy resources system in Home Energy Management System (HEMS)	User comfort is ignored
Evolutionary Algorithm (EA) [12]	Cost reduction	Energy optimization in household, commercial and residential consumption areas	System complexity is increased
Integer Linear Programming (ILP) [13]	Cost and *PAR* reduction	Categorizing/classification of household contrivances using day ahead pricing model	*PAR* is not considered
Dynamic Programming (DP) [14]	Cost and *PAR* reduction	Energy consumption behavior optimization with high penetration of renewable sources	System complexity is increased, user comfort is ignored as well
Genetic Algorithm (GA) [15]	Cost reduction and user comfort	Division of operation period, as a result cost reduced and energy is optimized	System deals with large number of contrivances in multiple sectors results in enhancement of system complexity
Genetic Algorithm (GA), Binary Particle Swarm Optimization (BPSO), Ant Colony Optimization (ACO) [16]	Cost and *PAR* reduction with limited user comfort	Using satisfaction and renewable sources integration considered, schedule the load	System complexity and computational time are increased
Genetic Algorithm (GA) [17]	Cost reduction and user comfort	Energy consumption behavior optimization using renewable incorporation	*PAR* is ignored and challenges in considering renewable sources are not addressed
Hybrid technique [Linear Programming (LP) & Binary Particle Swarm Optimization (BPSO)] [18]	Cost reduction and user comfort maximization	Interruptible contrivances are considered for schedule the operation under day ahead pricing umbrella	*PAR* is not considered
Fractional Programming (FP) [19]	Electricity cost reduction	Cost efficient model under distributed energy sources and practical implementation of the proposed model	*PAR* and user comfort are not considered
Genetic Algorithm (GA) [20]	Cost and *PAR* reduction	Radial electrical network model is used to test the proposed algorithm	System complexity and computational time is increased
Harmony Search Algorithm (HSA) [21]	Basic overview of Harmony Search Algorithm (HSA), its structure and applications	Improved and hybrid (Harmony Search Algorithm) HSA with applications	Real time implementation is not considered
Hybrid technique [Enhance Differential Evolution (EDA) & Harmony Search Algorithm (HSA)] [22]	Startup and generation cost of Renewable Energy Sources (RES)	IEEE standard bus system is used to verify the model	Computation time is increased
Binary Particle Swarm Optimization (BPSO) [23]	Minimization of energy cost considering user preferences	Simplicity and robustness of Binary Particle Swarm Optimization (BPSO)	Computational time increase with respect to division of time slots
Genetic Algorithm (GA) [24]	Minimization of energy cost, *PAR* and awaiting time	Generic model of DSM with Energy Management Controller (EMC) using RTP	User comfort is not addressed
Single knapsack [25]	Optimization of energy consumption using six layers architecture	Comprehensive model for energy management addressing six layers architecture	In real time and practical scenario, architecture become more complex

In time varying pricing tariffs, the proposed operation is divided into different time slots. The price of electricity varies according to different time slots. The prices are mainly higher from 6 PM evening to 10 PM night and lower at 12 AM night to 5 PM evening. Different pricing schemes as discussed in Khan *et al*. [26] are implemented by the utility on consumer. RTP is one of the major pricing schemes mainly used in European countries, in which the prices of electricity are declared after every hour for the next coming hour. Day Ahead Pricing (DAP) can be more effective because consumers can get sufficient times to plan their electricity consumption schedule, while hourly pricing can be boring for consumers. RTP can prove to be the most efficient pricing scheme, benefiting every stake holder involved and optimized by using the automated control system for the load [27]. The further type of RTP is DAP, in which prices of next 24 hours are defined day ahead. Second pricing scheme is Time of Use (TOU) pricing, which is mainly used in Indo-Pak region. In TOU pricing the prices are usually high at peak hours because high demand of energy, and low at off peak hours because low demand of energy. The more complex type of TOU pricing is seasonal TOU pricing in which prices varies according to season (two or more times in a year). Another important type which is considered to be more essential for DR is Inclining Block Rates (IBR). Inclining block rates structures charge a higher rate for each incremental block of consumption. As the consumption of energy increases, the rate of energy per kWh increases [28].

From all above previous literature we can draw a conclusion that:

- In all previous work, the RTP model is used in which prices are changed after every hour, as a reset and user struggle and have not a sufficient time to schedule the operation of his household load;
- No one method was proposed previously that takes into account all of three particulars, i.e. energy cost minimization, *PAR* reduction and user comfort. We proposed a model in which takes into account all of three particulars cost minimization, *PAR* reduction and user comfort without any complexity in system.

We proposed an algorithm that uses small number of contrivances to schedule the operation. In our system we take into account all of three particulars cost minimization, *PAR* reduction and user comfort. Our model will be simple and less complicated.

The rest of this paper is organized as: the system model is introduced in Section II. Problem formulation and algorithm description are presented in Section III. Simulation results are provided in Section IV. The paper is concluded in Section V.

SYSTEM MODEL

In this section, we present overall contribution towards this paper. We will define *PAR* according to parameters and its complete profile and impact on overall electrical system. Then we discuss of RTP and Pricing Function (PF) for our proposed model. Our system model is different from Khomami and Hossein Javidi [29], because in [29] RTP is to be implemented in such a way that prices are changed after every hour so that customer have insufficient time to schedule their load. In my system model i implemented such a RTP model that prices are not changed more than three times in a day. In such a model a customer have sufficient time to schedule the operation of their load according to demand.

Household load

Let us consider the residential setup that consist of 5 devices with variable energy consumption and categorized as in Table 2: must run and controllable devices that are interruptible and non- interruptible controllable devices. Must run start operation immediately at any time, e.g. PC, TV. Interruptible load is a controllable load. In this load it is not only possible to postpone the operation but also to interrupt the operation and restore later on, e.g. Plug in Electric Vehicle (PEV) [30-32]. Interruptible load further classified into two categories, sequential load and non sequential load. The operation period of sequential load is same for whole given 10 days, e.g. if it operation time is 5 AM to 6 AM then it will remain same. While the operation period of non sequential load is not in sequence, it becomes active any time in given period. In non interruptible load, the control unit may only delay its operation. For example, air conditioner timer and washing machine, etc. They complete their operation in specific time without interrupting or delaying their operation. The intended period of time for which i am going to develop algorithm is 10 days. Each hour is marked as one time slot and 1 day is equal to 24 hours means 24 time slots (t_s) so total numbers of time slots (T) are 24 × 10 = 240 time slots.

Table 2. Power rating for household load

Household devices	Power rating [W]
Device 1	2,000
Device 2	1,000
Device 3	746
Device 4	150
Device 5	60

Prices are defined for peak time and off peak hours, i.e. 13 PKR/kWh for peak time and 7 PKR/kWh for off peak time. Fist all calculation is to be done on given data without any Consumption Control Unit (CCU). CCU is nothing but a smart meter that has a digital two way intelligent communication infrastructure, and is responsible for DSM at consumer side. The whole system model is summarized such as:

- We developed narrative optimization based on inhabited model which reduce the energy cost for each residential consumer and reduce the *PAR* as well. Each device send operation signal towards CCU, CCU decides, signal could be acceptable or not according to demand of customer;
- We draw suitable management profile for controllable load in the sense of economically for the consumer and the electrical system;
- At last, we will make analysis on simulation results obtained from proposed algorithm. We see whether our algorithm effectively reduces the cost and *PAR* for overall aggregated load.

Peak to Average Ratio

PAR is the ratio of maximum aggregated load consumed in a certain time frame and the average of the aggregated load. *PAR* informs about the energy consumption behaviour of the consumers and the operation of the power grid. As we employed only the RTP, at peak hours when demand is high, *PAR* mainly increase which result in destabilization of electrical power grid. While reduction in *PAR*, simultaneously enhance the stability and reliability of power grid and reduces the electricity bill of residential consumers. *PAR* does not change as the customer does not respond to change the parameter which is defined in next sections. Mathematically, representation of *PAR* for a residential unit as in:

$$L_{\text{peak}} = \max_{t_s \in T} E_{\text{T}}(t_{\text{s}}) \tag{1}$$

$$L_{\text{avg}} = \frac{\sum_{t_{\text{s}}=1}^{T} E_{\text{T}}(t_{\text{s}})}{T} \tag{2}$$

where L_{peak} and L_{avg} show the maximum aggregated load and average load in a time frame (t_{s}), while $E_{\text{T}}(t_{\text{s}})$ represents the total energy consumption of devices in a time slot for intended operation. *PAR* is given by:

$$PAR = \frac{L_{\text{peak}}}{L_{\text{avg}}} = \frac{T \max_{t_s \in T} E_{\text{T}}(t_s)}{\sum_{t_s=1}^{T} E_{\text{T}}(t_s)} \tag{3}$$

Real Time Pricing

$\mathcal{P}_{t_s}$ is the total household power consumption in current time slot t_s. We define a pricing function (φ_{t_s}) with a combined model of RTP and IBR, which represent the wholesale payment in time slot t_s as a function of user's power consumption:

$$\varphi_{t_s}(\mathcal{P}_{t_s}) = \begin{cases} i_{t_s}, & \text{if} \quad 0 \leq \mathcal{P}_{t_s} \leq \mathcal{P}_{\text{th}} \\ j_{t_s}, & \text{if} \quad 0 \leq \mathcal{P}_{t_s} \leq \mathcal{P}_{\text{th}} \end{cases} \tag{4}$$

where i_{t_s}, $j_{t_s}$and $\mathcal{P}_{t_s}$ are the fixed parameters, and we have $i_{t_s} \leq j_{t_s}$. Discussed in next sections, combined model of RTP and IBR can effectively avoid load harmonization.

PROBLEM FORMULATION

Suppose that *D* represents the set of all devices present in this household unit, while *d* represents the current device on which operation is to be performed. Then each device $d \in D$ must act as either must run or controllable (interruptible or non-interruptible). The real time data is given in the form of 0 or 1, respectively, for all devices. We define a dual variable $\mathcal{Y}_{t_s}^{d} = \{0, 1\}$ as a representation of status of device $d \in D$. We set a variable $\mathcal{Y}_{t_s}^{d} = 1$ if the device *d* is active in current time slot t_s. In other case we set $\mathcal{Y}_{t_s}^{d} = 0$.

Without Consumption Control Unit

Schedule estimation. According to given data, the ON or OFF state for each device $d \in D$ with respect to time slots and days is given in Figure 1. From Figure 1, we analyze that device 1 is ON in each time slot in 10 days. For device 2 it can be seen that it is ON for all days in time slot 18 and for 7 days in time slots 12, 15 and 21. Device 2 is also ON for 4 days in time slots 6 and 9 and for 3 days in time slots 5, 7, 8, 10, 12, 13, 19 and 22, while at time slots 1, 2, 3, 4, 11 it remain OFF. In this way we check the device ON and OFF status in each time slot. Similarly, the ON and OFF status of all other devices can also be known easily by analyzing the Figure 1.

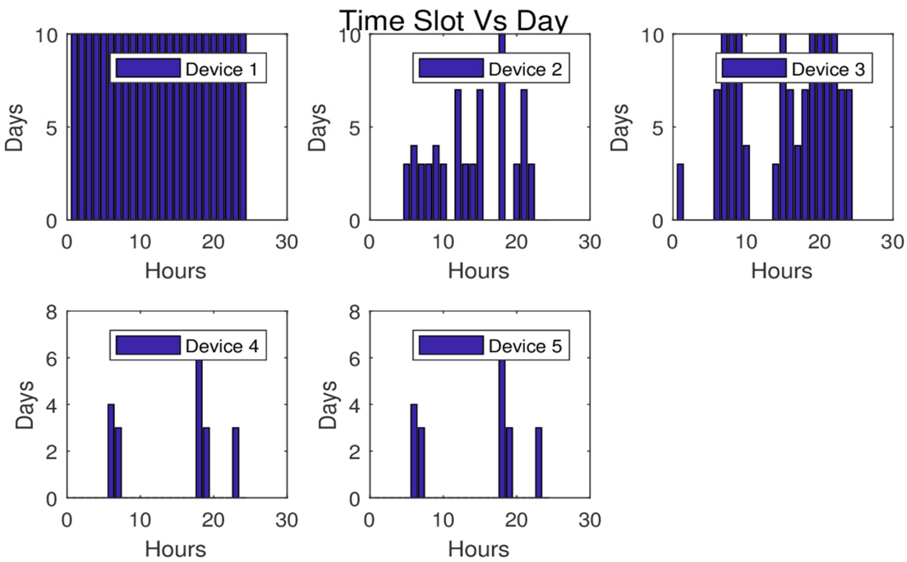

Figure 1. ON/OFF status of household load with respect to time slots and days

In device 3, it is seen that it remain ON for all 10 days in time slots 7, 8, 9, 15, 19, 20, 21 and 22 and 7 days in time slots 6, 16, 18, 23 and 24. Device 3 is also ON for 4 days in time slots 10 and 17 and for 3 days in time slots 1, and 14, while at time slots 2, 3, 4, 11, 12 and 13 it remain OFF. In device 4, it is seen that it remain ON for all 10 days in time slot 18 and for 4 days in time slot 6. It is seen that it remain ON for 3 days in time slots 7, 19 and 23 while except these time slots it remain OFF. Similarly, in case of device 5, it is seen that it remain ON for 7 days in time slot 18 and for 4 days in time slot 6. It is seen that it remain ON for 3 days in time slots 7, 19 and 23, while in remaining time slots it remain OFF.

Devices frequency. According to predefined variable $\mathcal{Y}_{t_s}^{d} = \{0, 1\}$, the state of ON or OFF and operation of overall load in given 240 time slots for given real time data 10 days is defined. Figure 2 tells us the overall frequency profile (on status) of each appliance for our monitoring system for all 240 time slots. We have 240 time slots in 10 days. From Figure 2, we can easily analyze that the device 1 is ON in all time slots, device 3 is ON in 130 time slots in 10 days, and device 5 is ON in 120 time slots.

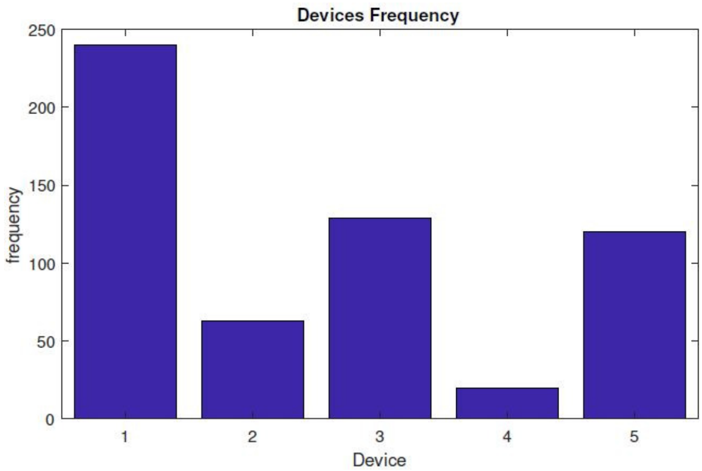

Figure 2. Devices frequency

Device 4 is ON for minimum time slots, i.e. 20 time slots for 10 days. In this way we check each device frequency for specific period of time in given days. And then estimate the overall household consumption for real time data and vice versa.

Load estimation. Let us denote that the whole intended operation period for all devices is T. We are going to calculate the power consumption of each device in their intended operation time slot cycle, i.e. $t_s \in T$. For that purpose we categorize the given household residential load into several classes that are given below and have been discussed in previous section as well:

- Must run load;
- Interruptible load;
- Non-interruptible load.

After categorizing the overall household load, we consider a system without CCU deployment, where each device d is assumed to start operation right after it becomes awake at its nominal power (α_d).

Figure 3 shows the variation in electrical demand over particular period of time. In Figure 3 we can see that wattage consumed curve of device 1 is a straight line because it remains on for all 240 time slots and does not show the variation in demand for a specific time due to must run property.

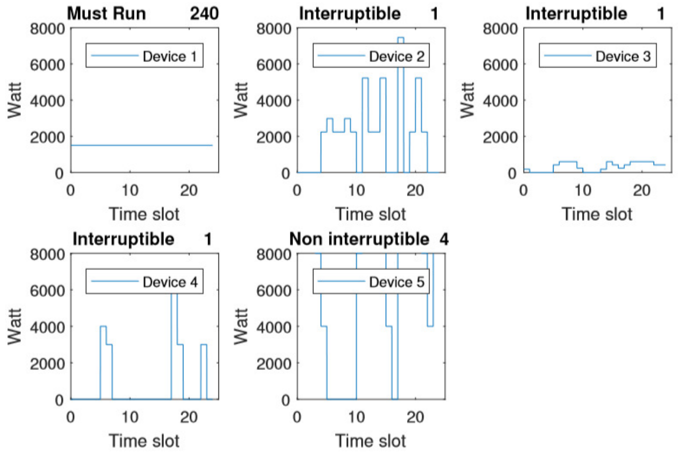

Figure 3. Power consumption profile of household load

Similarly, we can see in second interruptible device that it consumes maximum power of 7,500 W in time slot 18 for whole period of 10 days and consume 5,500 W for time slots 12, 15 and 21. Device 2 consumes 3,000 W in time slots.

Bill calculation. We note that the operation of different devices is influences by the preference of user. Different parameters of our model may be considered to capture different types of preference. In time differentiating pricing tariffs, the intended operation period is divided into several time slots, and the price of electricity varies across different time slots. For example, the prices may correspond to off peak, mid peak and on peak hours. We have different rates for energy consumption in RTP. In RTP, rates are defined at different levels of time slots, i.e. off peak hours where the energy rates are kept low because consumption is low and on peak hours where the rates are kept high because consumption increased during that time slots.

For above profiles the intended period of operation is divided into peak time and off peak time. Peak hours from 5 PM to 10 PM and the off peak or rest hours for the day are off peak hours (12 AM to 4 PM and 11 PM). According to RTP, the prices varies with time. We defined the prices, i.e. 13 PKR for peak time and 7 PKR for off peak time. According to that data we calculate the overall cost of all devices. From Figure 4, we can see that each device is consuming different power so the energy cost for each device is different. The device which has greater energy consumption bill in PKR represents that it starts operation many times during peak time slots because during peak time slots energy rates are high, i.e. 13 PKR per kWh.

Figure 4. Bill calculation when customer is informed by utility with respect to RTP

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So the total energy cost after summing energy cost of all devices is 3,269.65 PKR that is great amount by the way due to lack of energy CCU with our system. After calculating overall cost of consumption of all the devices in given 240 time slots (off peak and peak time), we move forward on the load estimation of our system. In our load estimation section we define how the load damages the overall system performance as well as in economical point of view of consumer. We discuss how we shift the load from peak time slots to off peak time to give incentive in economical point of view to the consumer and best for the community growth and infrastructure.

Load curve. Figure 5 explains the load curve for all devices collectively. In this way, we easily analyze the electrical demand in each time slot. This figure also shows the maximum and minimum electrical demand over a specific time for all the devices collectively. In figure we can see that the load is maximum at peak time slots and minimum at off peak time slots of total slots. As the consumption increases the calculated load increases, as a result *PAR* of a system increases and damage the system's performance.

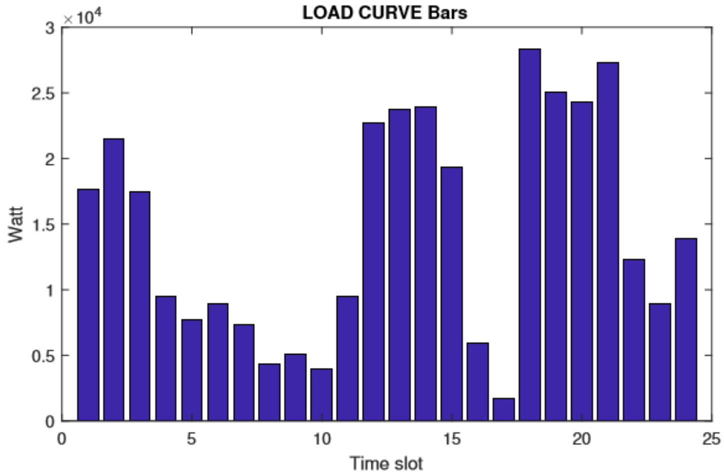

Figure 5. Histogram of *PAR* when only RTP is applied without CCU

Recall from eq. (3), *PAR* is the ratio of the maximum aggregated load consumed in a certain time frame and the average of the aggregated load. *PAR* informs about the energy consumption behaviour of the consumers and the operation of the power grid. In Figure 5 we can see that the load is consuming more power at time 18, 19, 20 and 21 during peak time slots (5 PM to 10 PM), where energy tariffs rates are high, which is not better for economical point of view for consumer. During these time slots the *PAR* is high which overload the electrical grid system and its performance is slowed down. Our aim is to minimize *PAR* to improve system performance to run smoothly. We also aim to shift the peak load to off peak time slots because the rates during off peak time slots are very low as compared to peak time slots to make economical use of energy in smart grid system.

Proposed strategy description

DSM through CCU deployment with RTP. When CCU is deployed with respect to RTP at demand side, the result in the form of DSM minimize the energy cost for residential user.

DSM through CCU deployment with RTP + IBR. When DSM is done through RTP, results in reduction in cost, but increases *PAR*, which damages the grid stability. For this purpose a combine model of RTP and IBR is implemented.

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Figure 6 is a block diagram of basic DSM scheme. From Figure 6 it is clear that CCU does not have any type of physical connection with must run load. It only schedules the controllable (interruptible and non-interruptible) household load according to the circumstances.

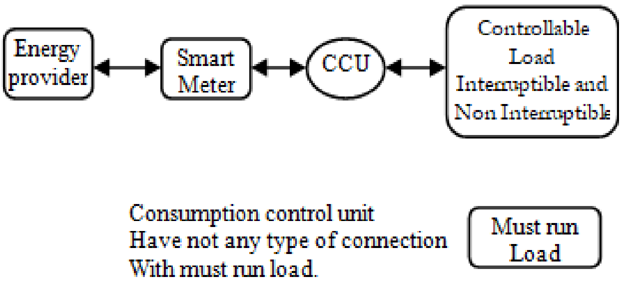


Figure 6. DSM through CCU

With Consumption Control Unit

When we deploy CCU, the operation signal is received from the device. Initially the load will be either must run or controllable. If the load is must run, CCU ignore it. When the load is shift-able (controllable), CCU accept the operation signal, once the operation signal is accepted the device starts its operation immediately. From Figure 7, in must run, device is in OFF mode and will remain OFF but when the operation signal is accepted it becomes ON and activate itself without any delay and finish operation. If the device is non-interruptible then again it is in OFF mode and obviously it remains in OFF mode.

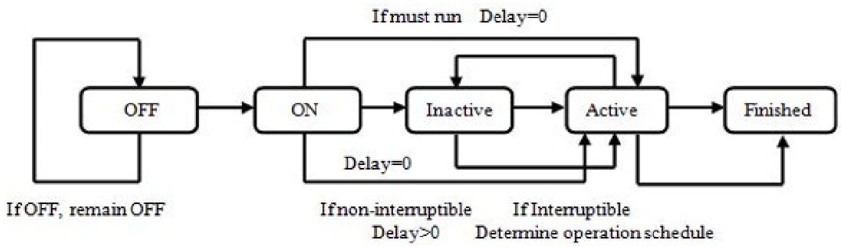


Figure 7. Different operating states of proposed algorithm

If it turns ON then a second inactive mode is developed. It goes to inactive mode with delay greater than zero and then active mode or directly from ON mode to active mode with zero delay and then finish the entered operation. If the device is interruptible controllable load, again if it is in OFF mode then it remains OFF. When it goes to OFF mode to ON mode it goes to inactive state. Now two states are developed, and performs dual operation between inactive and active modes or directly ON state to active state and then finish the operation.

Cost minimization. By deploying CCU, the load at the peak time slots, mainly 5 PM to 10 PM are shifted to off peak time slots to reduce the energy cost for residential users. Thus, we formulate a scheduling problem that minimizes the expected energy payment of the user with respect to demand uncertainties. In each time slot t_s as the demand information of the device is updated, the operation schedule of each controllable device can be rescheduled and the optimum power scheduling can be identified in real time as the solution of the following optimization problem for the minimization of expected cost from the current time slot t_s. In Figure 8 we can see that by deploying CCU energy, the energy is minimized, i.e. 2,771 PKR.

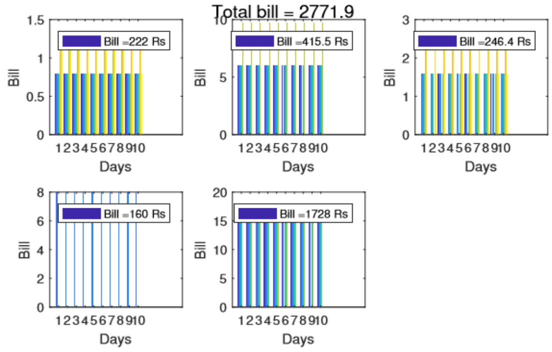


Figure 8. Cost minimization by deployment of CCU

Combination of RTP and IBR. When RTP is charged during peak time when the demands of energy are usually high, *PAR* of a system has been disturbed which obviously disturb the overall system's performance. To overcome this drawback and increase *PAR*, a combined model of RTP and IBR is implemented. According to Islamabad Electric Supply Company (IESCO), Pakistan, IBR are according to [33] as in Table 3.

Table 3. IBR set by regulation authority

Tariff category/Particulars	Prices per kWh
1-100 units	8.70 PKR
101-300 nits	10.20 PKR
301-700 units	14.00 PKR
Above 700 units	16.50 PKR

Peak to average ratio reduction. Let the demand information of the device is known ahead of time and awakes devices in the upcoming time slots $k > t_s$ that are currently sleeping, only the probability with each device becomes awake at each time slot before the operation cycle begins:

$$\sum_{t_s=1}^{T} p_{t_s}^{d} + q_d \tag{5}$$

where q_d denotes the probability that device d does not become ON at any time within the DSM operation period.

In Figure 9, we can see that after deployment of CCU energy, the bar line at peak time slots is shifted to off peak time slots. When the load from more energy consumption slots is shifted to less and reliable slots, then we have reduction in *PAR* of overall aggregated load which improves the overall system's performance.

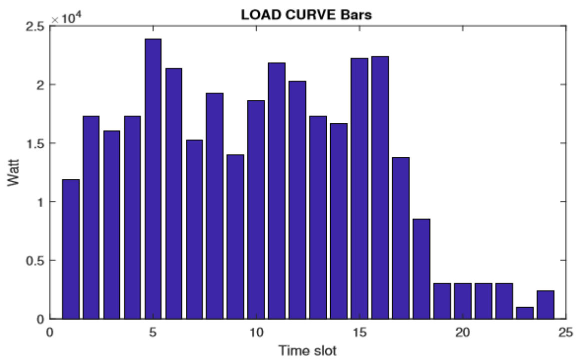


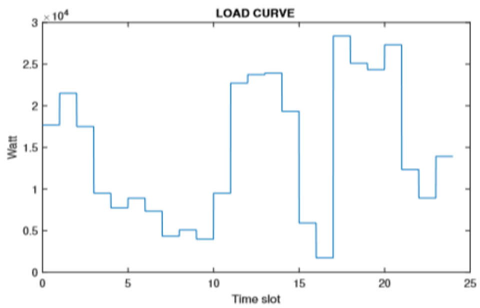
Figure 9. Reduction of *PAR* and shifting of pea values by using RTP + IBR

RESULTS

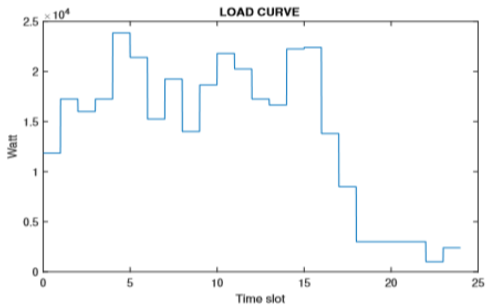
When we implemented only RTP, the energy cost is minimized but unfortunately we get increase in *PAR* of overall household load. But with involved IBR we got reduction in *PAR* ratio as well. In this section we describe the impact of involving IBR with RTP model.

Blow of involving Inclining Block Rates

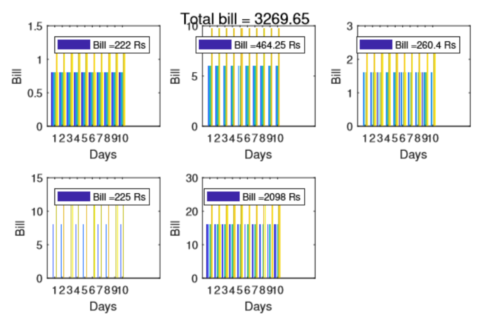
As in Figure 10, in RTP when pricing parameters changes from i_{t_s} to j_{t_s}, *PAR* of the system is disturbed. When $i_{t_s} = j_{t_s}$ then there will be no issue with *PAR* of the system. When it shows dual behaviour $i_{t_s} \rightleftharpoons j_{t_s}$ then IBR must be a part of our system. Simulation results for the average daily payment of the user as well as the average *PAR* of the system for different values of parameter are depicted in Figure 10. Intuitively, when parameter is equal to one, i.e. when $i_{t_s} = j_{t_s}$ for all time slots T, the performance of our proposed method is the same as the one in which effect of IBR is ignored. However, by increasing the pricing parameters, the payment increases, as the user has to pay more every time that its load exceeds threshold p_{th} as in Figure 10. Increasing pricing parameters improves *PAR* of the system. Surprisingly, results shows that greater the consumption, greater the cost and *PAR* reduction. So here we draw a statement that DSM encourages the user to use the power more wisely and effectively by shifting the load from peak time to off peak time. In my simulation model, p_{th} is set to (threshold power consumption level) 23.5 kW for 24 time slots. As the load exceeds the threshold point (23.5 kW), CCU shifts behind to off peak slots and that results in reduction in *PAR*.



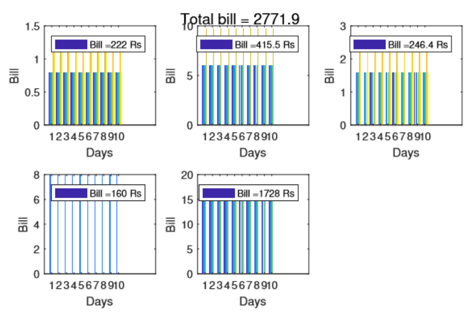
(a) without deployment of CCU



(b) with deployment of CCU



(c) without deployment of CCU



(d) with deployment of CCU

Figure 10. Difference between two profiles of *PAR* and cost without and with CCU

The overall comparison profile of system without and with deployment of consumption control unit is depicted in Figure 10. The overall calculated comparative result in numeric form is illustrated in Table 4. Both profiles are depicted and differentiated before deployment of consumption control unit and after deployment of consumption control unit.

Table 4. Concluded results of cost and *PAR* reduction

Particulars	Without CCU	With CCU	Reduction [%]
Cost	3,269.65 PKR	2,771.9 PKR	15.22
PAR	2.80×10^4 W	2.35×10^4 W	16.07

CONCLUSIONS

In this paper, i developed a residential DSM algorithm in presence of load uncertainty. I measured the benefits for both residential customer and utility via minimizing the energy cost as well as *PAR*. I formulated an optimization problem to minimize the electricity payment for residential users in the situations where only an estimate of the future demand is available. I focused on a scenario where RTP is combined with IBR to balance residential load to achieve reduction in *PAR*. Scientific contributions of work have covered different areas. A simulation results shows that a unique model of RTP provides a sufficient time to schedule the operation more easily, in which prices are changed only 2 to 3 times in day instead of hourly fluctuation. In fact, proposed model of RTP is a new shape of RTP in class of dynamic pricings. A results show that the proposed algorithm reduces the energy cost for users, encouraging them to participate in DSM scheme. Exploiting IBR with RTP tariffs can help to avoid load synchronization, and the combination of general RTP method with my algorithm reduces *PAR* of the total load. The latter provides incentives for utilities to support implementing the proposed algorithm. So this is proper intelligent algorithm for economical use of energy in smart electrical network system.

In future i have aim to integrate the renewable sources for more expediency of residential consumer. This will provide automatic switching to user during peak time slots. My system model can be extended to scenarios when a user faces deep trouble during load shedding. In this case of constraint of renewable sources can help to tackle this situation.

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Paper submitted: 02.03.2019
Paper revised: 19.06.2019
Paper accepted: 16.09.2019