Optimizing Efficiency of Home Energy Management System in Smart Grid using Genetic Algorithm

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Abstract:

A next-generation electrical power system known as the "Smart Grid" (SG) uses two-way communication to generate, use, and transport electrical energy. Demand Response (DR) is one of the SG's primary features (DR). Smart meters in DR transmit a pricing signal to the consumer, allowing them to adjust their demand in reaction to the corresponding price signals. Day-Ahead and Time-of-Use are the most widely used load scheduling schemes, however, they deviate from the Real Time Pricing scheme (RTP). Due to its erratic nature, integrating renewable energy sources like solar and wind is a difficult process in SG. Because of the fluctuations in both energy consumption patterns and power rates, the majority of current methods for managing demand are predicated either on day-ahead or time-of-use pricing rather than real-time pricing. This study describes a load scheduling system that uses a Genetic Algorithm (GA) to classify various users according to their energy use in a real-time pricing environment. Our load scheduling problem is formulated utilizing the knapsack mathematical formulation technique to reduce the electricity expenditure. In order to keep the grid stable and reduce costs, renewable energy is integrated with the grid's energy to lower the Peak-to-Average Ratio (PAR). The efficiency of the suggested algorithm in terms of electricity cost and PAR reduction is supported by simulation results.

Keywords: *Demand Response, Energy Management, Genetic Algorithm, Energy Optimization*

1. Introduction

Traditional Grid (TG) contains the network of efficient power transmission and distribution. In TG, when energy consumption demand is increased, it disturbs the grid stability by causing cascaded outage and load shedding. It motivates the research community to rethink about generating more energy in order to fulfill this energy demand. However, increasing power generation is not the ideal solution. With increase in generation, line losses raise thus disrupting grid economy in many ways. Therefore, an ideal solution has been proposed by scientists that effectively uses available energy. By adding two-way communication, information and control technologies, the transition from TG to Smart Grid (SG) is achieved. This transformation requires minimum modification in the infrastructure in the TG.

Demand Side Management (DSM) is the most important feature of SG [1]. In DSM the grid energy is utilized in such a way that it efficiently fulfills the consumer demand as well as improves grid stability by reducing PAR, which substantially enhances the grid economy. The primary component of DSM in SG is Demand Response (DR). Demand Response (DR) is the main feature of DSM in SG. It enables the user to alter its load

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consumption pattern in accordance to the electricity pricing signal. Because of the fluctuating nature of electricity price market, dynamic pricing schemes are the most significant feature of SG. The end users are then informed of these pricing plans through the integration of various communication technologies, allowing them to adjust their energy use in advance. Different dynamic pricing schemes for energy management are used in SG such as Day-ahead pricing, Time of Use, Real Time Pricing (RTP) and Critical peak pricing. However, except RTP, other pricing schemes only tell us about the estimated behavior of price signal [2]. Thus, the scheduling on the basis of this is not as efficient as the estimated price signal sometimes deviate from the original signal.

In this work we have used RTP signal for appliance scheduling. Now a days, integration of renewable energy sources with grid energy is frequently used in order to minimize the electricity bill. This integration shares the load burden of grid hence improving grid stability and reliability. The most effective method for addressing the issue of energy deficit is distributed generation. Although it is an effective solution to address all of these problems, it is exceedingly challenging to implement due to the intermittent nature of renewable energy sources.

In this paper, we present an efficient DSM technique dependent upon Genetic Algorithm (GA). Various types of loads with different operating constraints are considered in this work. Formulation of their constraints and global optimization problem is done by using 0-1 Knapsack mathematical technique. Hence, this optimization problem is tackled by using GA. Additionally, in-depth simulations are run to show the suggested algorithm's usefulness and efficiency.

2. Related Work

Recently, many Demand Side Management strategies have been presented. These DSM strategies are based on both heuristic and mathematical optimization methods. The basic purpose of all is to minimize the monetary expense of consumer and PAR to improve grid stability and economy.

In [3], different types of loads such as residential, commercial and industrial; loads are managed by using an evolutionary algorithm. An objective function is formulated whose aim is to bring the load curve near to the formulated objective curve. This curve is basically the reciprocal of the given price signal. The results show that the proposed algorithm efficiently handles the heuristics of the loads, which are challenging for any mathematical optimization technique to handle due to their complexity. This proposed algorithm also efficiently reduces the PAR and electricity bill.

In [4], an approach to predict weak points and failure modes in power grids by minimizing load shedding is introduced. The algorithm identifies high probability load configurations, known as instantons, on critical nodes and links. The method optimizes generator capacity and improves grid reliability. This approach has potential for enhancing power grid stability and addressing statistical challenges in the field.

An Integer Linear Programming (ILP) based load scheduling scheme is proposed in [5]. In this work the load isshifted from on to off- peak to minimize the electricity bill and PAR. Results show that the scheme performs well in a givenscenario

[6] Explores the application of wireless sensor networks (WSNs) in electric power systems, focusing on their integration into smart grid technology. The study includes extensive experimental investigations conducted in real-world power delivery and distribution systems, providing valuable insights and informing design decisions for WSN-based smart grid applications.

[7] Demonstrates the practical application of a novel energy planning methodology, INVERT, developed under the European Programme ALTENER in simulating various RES technologies and assessing their impact on transfer costs and CO2 emissions. The results highlight the potential for more efficient promotion of RES technologies in the electricity sector, providing valuable insights for future energy planning strategies.

In [8], a model for simulating electricity auctions with demand-side bidding (DSB) in the competitive power pool (CPP) framework has been introduced. DSB allows customers to actively participate in price determination by submitting bids for load reductions during specific periods. The study employs a specially developed Lagrangian relaxation scheme to simulate electricity auctions with DSB and effectively exploit the problem's structure. Numerical results from a 24-hour simulation on a small system contribute to a deeper understanding of the benefits and outcomes associated with incorporating DSB into electricity auction mechanisms, offering valuable insights for policymakers, market participants, and researchers to enhance the efficiency and effectiveness of electricity markets.

In [9], A system architecture is proposed to integrate renewableenergy in the system. A brief introduction of DSM components is discussed in this paper. DSM problemis formulated and an algorithm is then proposed to solve this problem. Results show that proposed algorithm efficiently manages the load in the presence of renewable energy source. In [10], a mathematical Linear Programming (LP) based optimization problem for home energy management is proposed. Optimization-based Residential Energy Management (OREM) algorithm is proposed in this paper to solve the mathematicalformulation. The purpose of this is to minimize the cost andPAR. This is a novel approach in a way that it considers the user comfort. Results show that it performs good. Another mathematical Monotonic optimization technique is proposed in [11]. A centralized renewable energy source is modeled and utilized in this work. Results show that the integrationof renewable energy source significantly reduces the cost andPAR. A Mixed Integer Linear Programming (MILP) [9], based optimization problem formulation and solving technique is proposed. The purpose of this is to control the various types of appliances with different operational constraints to reduce the electricity bill. Results show that the technique performs well.

Another strategy to prevent distribution system overloading is proposed in [12]. In this work, load is prioritized according to the user demand which means if the aggregated load on distribution transformer exceeds, the central controller takes actions and shuts down the load with lowest priority. For a test case, large penetration of electric appliances are considered in this work. In case of their charging time when load exceeds, the overloading is avoided by proper load scheduling. However, it is autonomous approach to save secondary distribution system but instead of load scheduling, load shedding mechanism is adopted in this work.

In [13] Optimal Stopping Rule (OSR), mathematical optimization technique is used to formulate the price threshold foreach type of load. The controller takes decision by comparing price value with this calculated threshold. In this work, the appliance waiting time is also modeled. This scheme reduces the electricity cost as well as appliance waiting time. It schedules the appliance according to its priority, higher the priority, lesser the waiting time.

Methods that have been mentioned above are originated by using ILP, LP, MILP and OSR but are complex in handling a large number of appliances and their parameters. Further- more, mathematical optimization techniques perform betterin modelling, but for implementation point of view they are very complex [14]. Therefore, evolutionary algorithm such as GA performs well in this situation as it tackles all the heuristics of the problem in a better way.

The remaining part of this paper is organized in a way that model of system and formulation of problem is provided in Section III, Section IV presents Proposed DSM algorithm, Section V gives us Results and Discussions, lastly section VI summarizes the paper.

3. SYSTEM MODEL AND PROBLEM FORMULATION

We assume an autonomous home with three different kinds of loads i.e., Base Loads (BL), Discrete type Loads (DL), Continuous type Loads (CL) and Residential Energy Source (RES). The power consumption of each type of load depends upon different operation constraints and their duty cycle [19]. The devices known as BL (TVs, Computers, Lights, Bulbs, etc.) operate anytime a user sends the controller an ON request even though they cannot directly participate in the DR programme. The ones that turn ON when the price is cheap or RES is available are CL (AC, water pump, etc.). Once these type of loads turn ON, they must complete their duty cycle. Whereas, DL (Microwave, Dishwasher, Washing Machine, etc.) are adaptable in nature with an interruptible duty cycle [15].

A. Energy Consumption Model

Every appliance type has a unique pattern of energy usage. Each appliance first share its appliance type with EMC, on the basis of this information EMC schedule these appliance accordingly thus calculates the overall electricity bill.Consumption profile for energy of user is calculated as follows.

$$\boldsymbol{\varrho^T} = \sum_{t=1}^{24} \sum_{i=1}^{n} \sum_{j=1}^{m} \boldsymbol{\delta_{ij}}\,(\boldsymbol{t}) \times \boldsymbol{\varrho_{ij}}(\boldsymbol{t}) \quad (1)$$

$\boldsymbol{t}$ Time slots.

$\boldsymbol{i}$ Number of appliances.

$\boldsymbol{j}$ Type of appliance.

$\boldsymbol{\varrho_{ij}}$ Consumption of energy of appliance $\boldsymbol{i}$ of type $\boldsymbol{j}$.

$\boldsymbol{\delta_{ij}}$ ON/OFF State of appliance $\boldsymbol{i}$ of type $\boldsymbol{j}$

B. RES Model

We assumed that the user is equipped with RES. The user partially generates its own energy which results in PAR and cost reduction. Instead of wind turbines, photovoltaic panels (PV) are preferred for offshore areas. Therefore, in this work we make the assumption that the home is equipped with PV panels and generates the partial user energy demand. Solar radiation, which is intermittent by nature and varies month to month, is often the basis for PV generation. Solar radiations, panel direction, area, and efficiency all play a role in solar power of panels. The hourly generation solar energy is calculated byusing following expression [12].

$$\boldsymbol{\varepsilon(t) = 10} \times \frac{\mathbf{1}}{\sqrt{\mathbf{2\pi\sigma}}} \boldsymbol{exp}\left(^{-\frac{(t-\mu)^2}{2\sigma^2}}\right) \quad (2)$$

where, σ^2 is variance and μ is the mean of distribution. It isconsidered that $\varepsilon(t) = 0$ at night and $\varepsilon(t) > 0$ at day time.

C. Energy Consumption Cost Model

We assume that the price signal is real time in nature. The electricity bill of the user is calculated by simply multiplying the hourly price signal ζ with the energy consumption of user at that time slot. So, the energy consumption cost is calculated as follows.

$$\boldsymbol{\Omega^T} = \sum_{t=1}^{24} \sum_{i=1}^{n} \sum_{j=1}^{m} \boldsymbol{\delta_{ij}}\,(\boldsymbol{t}) \times \boldsymbol{\varrho_{ij}}(\boldsymbol{t}) \times \boldsymbol{\zeta}(\boldsymbol{t}) \quad (3)$$

D. PAR Calculation

Reduction in PAR is beneficial for both user and power providing companies. If PAR is reduced, the peak power plant at grid level is reduced and for user it's beneficial in terms of price signal which depends on aggregate energy usage of the consumers. PAR is calculated by simply dividing the peak load with average load, which is as follows.

$$\boldsymbol{\Delta} = \frac{\boldsymbol{max\delta(t)}}{\frac{1}{24}\sum_{t=0}^{24}\delta(t)} \qquad (4)$$

E. Objective Function

In this subsection, the load scheduling problem is formulated by using 0-1 Knapsack mathematical formulation technique. This mathematical formulation technique allowsus to limit the user energy consumption demand in order to minimize the PAR. The energy consumption cost minimization problem is formulated as follows.

Minimize

$$\sum_{t=1}^{24}\sum_{i=1}^{n}\sum_{j=1}^{m}\boldsymbol{\delta_{ij}(t)\times\varrho_{ij}(t)\leq\lambda(t)} \qquad (5)$$

Subject to

$$\sum_{t=1}^{24}\sum_{i=1}^{n}\sum_{j=1}^{m}\boldsymbol{\delta_{ij}(t)\times\varrho_{ij}(t)\leq\lambda(t)} \qquad (5a)$$

$$\sum_{t=1}^{24}\sum_{i=1}^{n}\sum_{j=1}^{m}\boldsymbol{\delta_{ij}(t)} = \mathrm{LOT}_{ij} \qquad (5b)$$

$$\boldsymbol{\gamma_i} \leq 24\text{-}\mathrm{LOT}_i \qquad \forall \boldsymbol{DL} \qquad (5c)$$

$$\boldsymbol{t_s^i} \leq \boldsymbol{\gamma_i} \leq \boldsymbol{t_s^i} + \mathrm{LOT}_i \qquad \forall \boldsymbol{CL} \qquad (5d)$$

$$\boldsymbol{\gamma_i} = \boldsymbol{t_s^i} \qquad \forall \boldsymbol{BL} \qquad (5e)$$

$$\boldsymbol{\Delta}_{Scheduled} < \boldsymbol{\Delta}_{Unscheduled} \qquad (5f)$$

$$\boldsymbol{\varrho^T}_{Scheduled} < \boldsymbol{\varrho^T}_{Unscheduled} \qquad (5g)$$

$$\boldsymbol{\delta} \in \{\boldsymbol{0},\boldsymbol{1}\} \qquad (5h)$$

LOT_{ij} is the number of ON request of appliance i of type j, i-e duty cycle and $\lambda(t)$ is maximum power limit at time slot t.

4. ALGORITHM PROPOSEDFOR DSM

We consider RES-equipped building. The efficiency of the suggested algorithm is illustrated using three different classes of controllable loads. This building has numerous appliances having various parameters including distinct *LOTs*, energy usage and interruption priorities based on load types. The DSM controller connects with different types of appliances and generation unit thereby sharing the *base load* demand with the generation unit to accommodate it. Also, each load share has a specific kind of load, i.e., either it is *base*, *discrete* or *continuous load*. The DSM controller then schedules various types of loads in order to reduce the electricity bill, peak load, and user annoyance. All of these heuristics can be accommodated by GA. GA has superior computational capabilities and convergence rate as compared to other mathematical methods [3].

In GA, we are majorly interested in population's chromosomes, because they provide the solution to our problem. In this case, chromosomes are the array of bits of length equal to the number of appliances, which shows the *ON/OFF* state of the appliance. Thus, we are dealing with *N* number of controllable appliances which is length of the chromosome *N*. The major steps of GA are discussed below

Initial Population: The first stage of GA algorithm is to randomly initialize the population; this population will have one candidate solution called chromosome. The dimensions of initial population are varied according to user preference; which means greater the population, more precise the solution. But as the population grows, the algorithm becomes more complex. The initial population is *M*×*N*, where *M* represent population size and *N* represent number of appliances.

Fitness Evaluation: In this step, evaluation for fitness is done for each chromosome. For demonstration, we consider that the chromosome is [0 1 0 1 0 0] which represents that the appliances 1, 3, 5 and 6 are turned OFF and appliances 2 and 4 are turned

ON by the algorithm according to objective function. In this work, the respective states of appliances are first multiplied with their corresponding energy usage, and then the cumulative power consumed in a single time slot is thus used to determine the electricity bill. However, the best chromosomal design chosen for further examination is the one with the lowest electrical cost .Fitness function is evaluated as follows.

$$\text{Fitness}=\sum_{t=1}^{24}\sum_{i=1}^{n}\sum_{j=1}^{m}\boldsymbol{\delta_{ij}(t)}\times \boldsymbol{\varrho_{ij}(t)}\times\boldsymbol{\zeta(t)} \qquad (6)$$

Selection: Random population for fitness evaluation is selected only once in the whole algorithm. Further new population is obtained by cross over and mutation. For this new population, any two chromosomes are randomly chosen from the previous population to produce a new offspring using cross over and mutation of the parent chromosomes.

There are many methods for this selection. However, in this work we select method based upon tournament concept [17] [18].

Cross over and Mutation: There are many ways with which Crossing over and mutation can be done. In this study, we have used binary mutation and single point cross over due to the fact that our scheduling problem is discrete in nature. Convergence refers to the point at which an algorithm discovers its ideal answer and it depends upon the two steps of the algorithm (cross over and mutation). If cross over rate is increased the convergence is fast, but it takes longer if mutation rate is increased since the optimal solution may get lost and hence results in slow convergence.

Elitism: It is not mandatory to find the solution just after convergence and mutation following fitness evaluation. It's feasible that we find our ideal solution in the first phase because of the population's random generation. Due to the generation of population randomly, a possibility arises that we get our desired solution in the initial step. However, the chances exist that after cross over and mutation of such a chromosome we may lose optimal solution. Elitism, therefore; enables us to maintain this solution for the following population, ensuring that it compares with the new population and endures until the end. The proposed DSM Flow chart is shown in Figure 1.

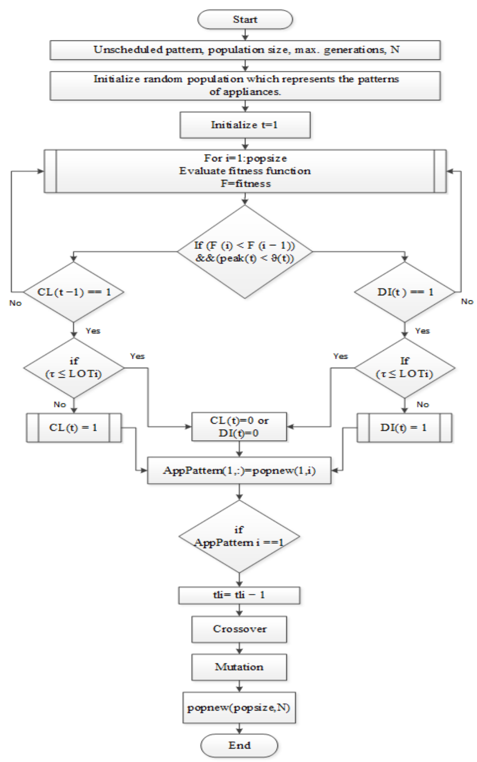

Fig. 1. Flow Chart

5. RESULTS OF SIMULATION AND DISCUSSIONS

This section discusses the results of simulation as shown in Table 1. MATLAB (R 2017a) has been used for simulation purposes. We assume an autonomous home with various loads. The different load parameters are discussed in Table 2.

Table I. Parameters of GA

Parameters	Value
N	6
Max. Generations	500
Population size	200
Pc (Cross-over Rate)	0.7
Pm (Mutation Rate)	0.3

Table II. Load Parameters

Load Type	**Loads**	**LOT (t)**	**Energy consumption (kWh)**
Base Load	load 1	20	1
	load 2	24	1.5
Discrete Load	load 3	5	2
	load 4	7	2.5
Continuous load	load 5	8	3
	load 6	8	3.5

The price signal is assumed to be an RTP signal and is taken from [3], shown in Figure 2. It is clear from Figure 2, that the price is varying in 1 hour time slot. Figure 3 illustrates the RES hourly generation with and without efficiency. It is clear from Figure 3 that generation depends on the irradiations and the temperature, as it is maximum at day time and approaching at night time. Generally, the solar power generation efficiency is considered as 18 to 22% [16]. Hence, in this work, we have considered 22% solar generation efficiency. Solar generation is obtained byusing equation (2).

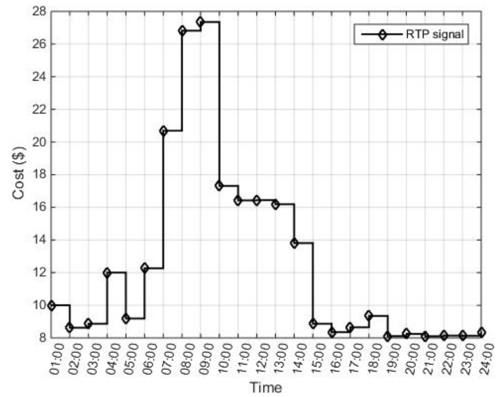

Fig. 2. RTP Signal

The energy consumption profile of user is shown in Figure 4. It is illustrated from the figure that DSM controller performs well and schedules the load efficiently. The DSM controller modifies the energy consumption profile of the user in response respectively

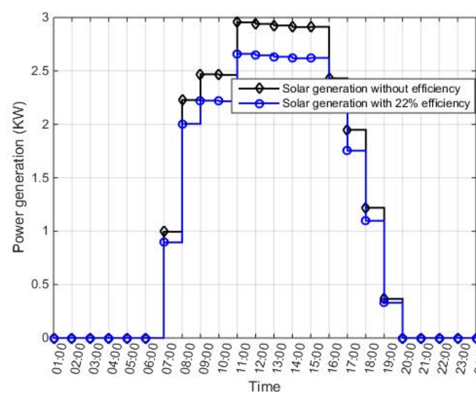

Fig. 3. RES Generation

to RTP signal to reduce its monetary expenses. Also, it is clear from the Figure 4 that controller also manages the load in a manner that the load peaks get reduced. With the integration of renewable energy source, the controller shares the grid energy with the renewable energy. This mechanism further reduces the electricity bills and PAR. This mechanism motivates the consumers to install RES in their homes which further improves grid stability and hence the electricity price market stability.

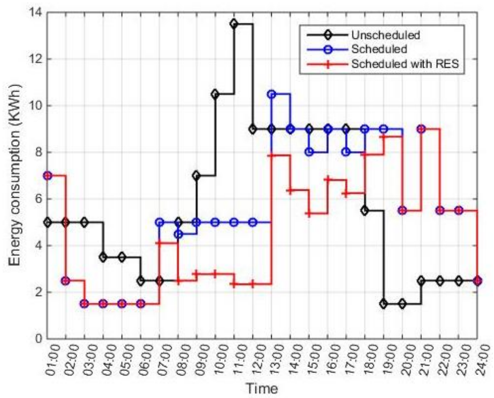

Fig. 4. Energy Consumption Profile of User

The daily electricity consumption cost profile is displayed in Figure 5. This Figure 5 clearly shows that after scheduling the bill is reduced. However, it is achieved by only transferringthe load in off-peak hours instead of traditional load shedding. The total energy consumption in case of scheduled and unscheduled load remains same. The monetary saving is efficiently achieved only by modifying the energy consumption profile.

Results verify that the electricity bill is significantly reduced in case of simple scheduling and scheduling with RES.

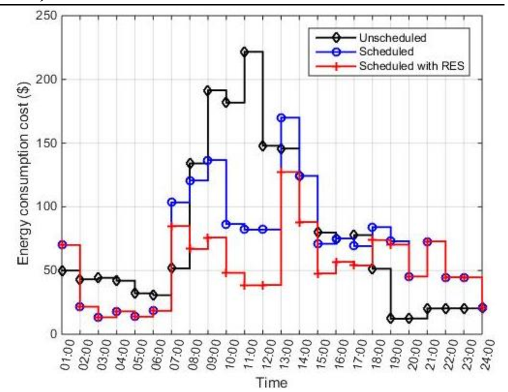

Fig. 5. Energy Consumption Cost Profile of User

Total electricity bill calculation of user is shown in Figure 6. Results are compared with unscheduled, scheduled and scheduled with RES. Result shows that the proposed algorithm performs efficiently in all conditions. The electricity bill is reduced from $1832 to $1662 $ in case of scheduling without RES,which is about approximately 9.27 % reduction in electricity bill. On the other hand, in case of scheduling with RES, the electricity bill is reduced from $ 1832 to $ 1255, which is about 31.49 % reduction in electricity bill as comparedto unscheduled load and 24.48 % reduction as compared to scheduled load without RES. These results depict that the integration of renewable energy source has a large impact on DSM program, and is beneficial for both user and utility.

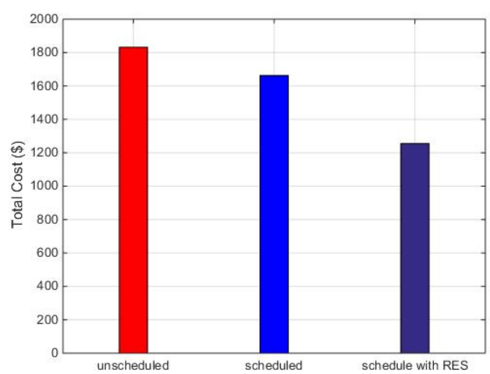

Fig. 6. Daily Total Electricity Bill of User

Moreover, results in Figure 7 show the reduction in PAR. Figure 7 clearly shows that the PAR is approximately 22 % reduced after scheduling. And with the integration of RES, the PAR is further reduced to approximately 33 %, which is1 0 % more reduction than the scheduled load without RES. This reduction creates a significant impact on grid stability and reliability. The reduction in PAR results in cost saving of peakpower plants for the power providers. The electricity price regulatory authority also regulates the electricity pricing based on consumption of energy of the consumers. If PAR gets reduced the price value is also reduced for the upcoming time slots.

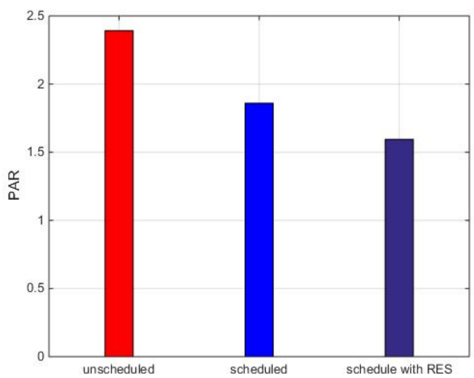

Fig. 7. PAR Calculation

6. CONCLUSION

In this work, a DSM algorithm is presented for home energymanagement. The purpose is to take PAR and cost reduction into consideration. For the sake of simulation purpose, we consider three kinds of appliances having distinct energy and operating limits, as well as the incorporation of a renewable energy source. First of all, the availability of RES is checked by algorithm for itsoptimal utilization. If RES is unable to fulfill the complete demand of load, then the controller schedules this appliance based upon RTP signal. Outcomes demonstrate that the algorithm presented performs efficiently by reducing the cost and PAR. The proposed strategy saves financial cost by 31% with RES utilization and 9% without RES use. Moreover, the PAR is reduced to 22% without utilizationof RES and 33% with utilization of RES respectively.

REFERENCES

[1] Ożadowicz, Andrzej. ”A new concept of active demand side management for energy efficient prosumer microgrids with smart building technolo- gies.” Energies 10, no. 11 (2017).

[2] Chen, Yung-Yao, Yu-Hsiu Lin, Chia-Ching Kung, Ming-Han Chung, and I-Hsuan Yen. ”Design and implementation of cloud analytics-assisted smart power meters considering advanced artificial intelligence as edge analytics in demand-side management for smart homes.” Sensors 19, no.9 (2019).

[3] Nawaz, Abdullah, Ghulam Hafeez, Imran Khan, Khadim Ullah Jan, Hui Li, Sheraz Ali Khan, and Zahid Wadud. ”An intelligent integrated approach for efficient demand side management with forecaster and advanced metering infrastructure frameworks in smart grid.” IEEE Access (2020).

[4] M. Chertkov, F. Pan and M. G. Stepanov, "Predicting Failures in Power Grids: The Case of Static Overloads", IEEE Transactions on Smart Grid, vol. 2, no. 1, (2011), pp. 162-172

[5] Li, Zhengmao, Yan Xu, Xue Feng, and Qiuwei Wu. ”Optimal stochastic deployment of heterogeneous energy storage in a residential multienergy microgrid with demand-side management.” IEEE Transactions on Indus- trial Informatics 17, no. 2 (2020).

[6] VC Gungor, Bin Lu, and GP Hancke. Opportunities and challenges of wireless sensor networks in smart grid. Industrial Electronics, IEEE, 57(10):3557–3564, 2010

[7] Tsioliaridou E, Bakos GC, Stadler M. A new energy planning methodology for the penetration of renewable energy technologies in electricity sector – application for the island of Crete. Energy Policy 2006;34(18):3757–64

[8] Strbac, G., Farmer, E.D., Cory, B.J., “Framework for the incorporation of demand-side in a competitive electricity market”, Proceedings of the IEEE Generation, Transmission and Distribution, vol. 143, no. 3, May 1996, pp: 232-237

[9] Elavarasan, Rajvikram Madurai, S. Leoponraj, J. Vishnupriyan, A. Dheeraj, and G. Gangaram Sundar. ”Multi-Criteria Decision Analysis for user satisfaction-induced demand-side load management for an

institu- tional building." Renewable Energy 170 (2021).

[10] Singh, Shashank, Amit Roy, and M. P. Selvan. "Smart load node for non-smart load under smart grid paradigm: A new home energy management system." IEEE Consumer Electronics Magazine 8, no. 2 (2019).

[11] Li, Xiaozhu, Weiqing Wang, and Haiyun Wang. "A novel bi-level robust game model to optimize a regionally integrated energy system with large- scale centralized renewable-energy sources in Western China." Energy 228 (2021).

[12] Wang, Xiuwang, Xinna Mao, and Hossein Khodaei. "A multi-objective home energy management system based on internet of things and opti- mization algorithms." Journal of Building Engineering 33 (2021).

[13] Kumar, R. Seshu, L. Phani Raghav, D. Koteswara Raju, and Arvind R. Singh. "Impact of multiple demand side management programs on the optimal operation of grid-connected microgrids." Applied Energy 301 (2021).

[14] Manojkumar, Rampelli, Chandan Kumar, and Sanjib Ganguly. "Optimal Demand Response in a Residential PV Storage System Using Energy Pricing Limits." IEEE Transactions on Industrial Informatics 18, no. 4 (2021).

[15] Ma, Yanhong, Qingquan Lv, Ruixiao Zhang, Yanqi Zhang, Honglu Zhu, and Wansi Yin. "Short-term photovoltaic power forecasting method based on irradiance correction and error forecasting." Energy Reports 7 (2021).

[16] Reinders, Angèle, Pierre Verlinden, Wilfried Van Sark, and Alexandre Freundlich. Photovoltaic solar energy:from fundamentals to applications. John Wiley & Sons, 2017.

[17] Awais, Muhammad, Nadeem Javaid, Nusrat Shaheen, Zafar Iqbal, Ghazanfar Rehman, K. Muhammad, and Iftikhar Ahmad. "An efficient genetic algorithm based demand side management scheme for smart grid." In 2015 18th international conference on network-based information systems, pp. 351-356. IEEE, 2015.

[18] Bakare, Mutiu Shola, Abubakar Abdulkarim, Mohammad Zeeshan, and Aliyu Nuhu Shuaibu. "A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction." Energy Informatics 6, no. 1 (2023): 1-59.

[19] Chen, Jingxiao, Gaodan Deng, Lei Zhang, and Ali Ahmadpour. "Demand side energy management for smart homes using a novel learning technique–economic analysis aspects." Sustainable Energy Technologies and Assessments 52 (2022): 102023