Evaluation of Optimization Algorithms for Customers Load Schedule

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Abstract—**This paper introduces a novel concept for customer load scheduling in the Smart Grid (SG). The concept is based on the forthcoming internet of things (IoT). Approximate optimization algorithms are deduced for optimum customer load scheduling, maximization of electric power suppliers performance, and fairness in scheduling customers load. Using these approximate optimization algorithms as constraints, some loads are given priority. Other loads are scheduled in order to control the maximum demand load and electricity bills. To evaluate the effectiveness of the algorithms, we utilize the Mixed Integer Linear Programming (MILP). Simulations are carried out and the impact on reducing the peak-to-average power ratio (PAPR), the electricity bills, and ensuring fairness in customers load schedules are investigated. Simulation results establish that our algorithms significantly cut down on electricity bills, maximizes utility performance, and deliver fairness in customers load schedules..**

Index Terms—**demand response (DR), electric vehicle (EV), internet of things, load scheduling, mixed integer linear programming, optimization algorithms, power management system (PMS) and smart grid.**

I. Introduction

THE future of the traditional electricity grid is the SG. There are many reasons to locomote the electricity grid architectures from centralized, closed power systems to smarter, highly automated power grids [1], [2]. Todays power systems are designed to meet peak power demands. However, this peak power can be much higher than the average power consumption. Power systems can be said to have high PAPR energy requirements [3]. This problem is expected to worsen as EV hit the streets at a faster rate in the coming years [4]. This requires the concept of Distributed Generation (DG) and the use of renewable energy sources (RES) such as wind turbines and solar cells to generate additional and cleaner energy [5]. In addition, the excess energy generated can be stored for later use. This is done by connecting the energy storage elements to the power grid. One of the main characteristics of SG is the optimal adaptability to efficiently meet temporal requirements [6]. This characteristic reflects SGs intelligent character.

There are many levels of energy management in SG. The power management schedules between resources (solar, wind, storage, micro-grid, etc.) to achieve specific goals such as meeting load requirements, minimizing costs, and maximizing the performance of the power suppliers [7]. To achieve these objectives in terms of the market value of electricity, the concept of DR is used. A program that utility companies implement to allow controlled access to consumer devices is called Demand Side Management (DSM) [4] and it simplifies energy demand according to customer demands [5]. Some objectives like reduction of electricity bills, peak power demand, strategic load growth, flexible load shape, peak clipping, and load schedules are met with DSM [8], [9].

In existing works, DR concepts are explored from different viewpoints. In [10], [11], a MILP formulation is presented which optimally schedules the loads to reduce electricity bills within the limits of the scheduling requirements. The authors of [12] used convex programming to significantly reduce electricity bills and PAPR. In [13], [20], users are incentivizing to reschedule their power consumption patterns in order to reduce operating costs, but this requires the customer to change the desired load consumption pattern. The authors of [7] used game theory to investigate the DSM and presented a win-win situation between the utility and the customer. Gaur *et.al* [14] used a genetic algorithm to reduce the costs of PAPR and electricity bills. Reference [15] proposed a pricing model that takes fairness [20] into account. The paper shows how the demand curve flattens out over the course of the day. Nevertheless, the paper settled on a win-win situation between the utilities and the customer. Per the works above, customer satisfaction and fairness in load schedules are not guaranteed.

In this paper, we present customer load schedules based on our proposed PMS. We derived mathematical formulas to maximize utility performance, optimize load scheduling, and ensure fairness in load schedules. Our proposed algorithms give the customer the opportunity to adhere to the desired load pattern. The algorithms finally give customers the ability to determine the load that can be re-scheduled within the schedulable loads. Thus, granting fairness and customer satisfaction.

The rest of the paper is organized as follows; The proposed model is presented in Section II. Mathematical formulations for minimizing electricity bills, maximizing utility productivity, and fairness in scheduling customer loads are presented in Section III. Section IV presents performance analysis and Section V concludes.

II. Proposed Model

We consider the PMS of a Low Voltage (LV) power distribution network. The operational concept for the proposed PMS is shown in Fig. 2. In SG, energy can be obtained from various energy sources like hydropower, wind power, biomass, solar power, etc. Each source is labelled as power source PS_i The PMS decides how much power should be used from each power supply such as $0 \leq \mathrm{PS}_i \leq \mathrm{PS}_i^{max}$ where PS_i^{max} is the maximum power that can be drawn from each PS_i. However, the peak available power from all the power

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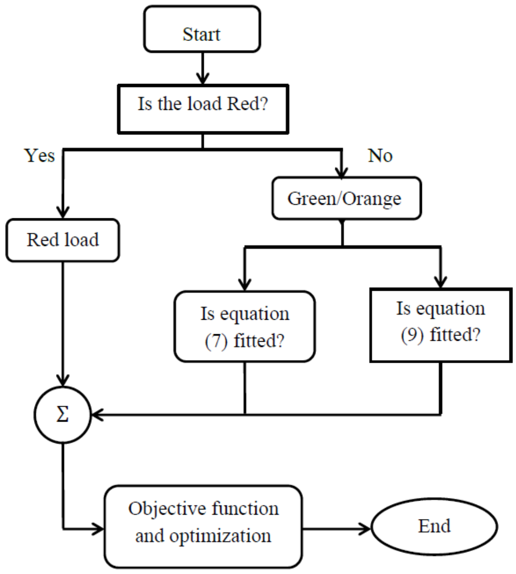

Fig. 1. Flow Chart of the Proposed Model

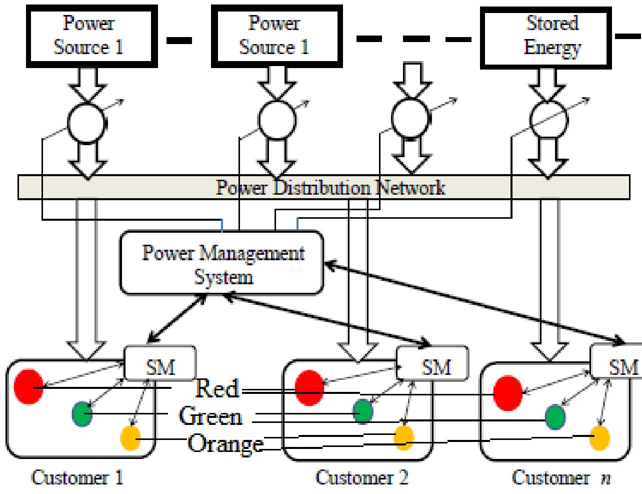

Fig. 2. Power Management System.

sources could be noted as P_t^{max}. The subject of an optimum selection of power sources to maintain certain objectives is very well researched as in [15], [16], [17].

We assume that the power sources are arranged in descending order in terms of available power. This means that the PMS will first meet the load requirements from a power source. If the load demand exceeds the available power of the supplying power source, it will automatically switch to supply power from the next power source, and so on. Each power source has a weight value ci . Weight value represents many parameters such as generation cost, environmental impact, and possibly, public policy. (e.g. importing power from other countries) [18].

In the PMS, each customer has three kinds of loads. Red loads represent loads that must have power supply whenever needed. Red loads are not schedulable in time regardless of the tariff or regardless of the power supply and demand balance [19]. There are several types of appliances that can be classified in this category. In either case, customers can classify which of their loads are red.

Orange loads represent the type of loads that must receive certain active periods during the day, but those periods can be rescheduled. There are three statuses for orange loads: preferred periods, non-preferred periods, and fair periods. Fair periods do not belong to a preferred period or a non-preferred period. An example of such orange loads is the washing machine with a non-preferred period of 22:00 - 6:00 due to the operational sound. Orange loads can be rescheduled to meet the customer requirements as well as the power supply-demand situation.

The green loads represent loads that can be scheduled without any time constraints. Green loads can be scheduled to meet customer requirements along with the total cost of electricity and to manage the power supply-demand balance. As a result, the electric power supplier must optimize the distribution of tariffs over time according to demand and supply conditions. Higher tariffs for peak periods and lower tariffs for off-peak periods encourage customers to voluntarily reallocate orange and green loads. However, the effectiveness of scheduling the orange and green loads are major indicators of electric power company performance and reputation. We assume a monopsony system where electric power companies compete for customers. Therefore, the Quality of Service (QoS) of electric power suppliers is an essential parameter to reflect customer satisfaction. Any electric power supplier that does not consider the green loads in energy management seriously will cause customer dissatisfaction, which can lead to massive migration to other electric power suppliers. In addition, the allocation of very high tariffs for peak periods can also lead to customer dissatisfaction. Thus, optimal scheduling is a very critical issue for the electric power suppliers. Optimal scheduling will help maintain a stable system even during peak demand periods and help customers cut down electricity bills.

Failure probability can also be defined as the possibility of remotely disconnecting loads (orange or green) during normal operation to resolve critical technical problems. This is also a parameter for accessing QoS. Red loads are not included in the failure probability, as they should not be included in any load scheduling. However, this may happen due to a sudden supply interruption. In general, for the power suppliers it is important to consider the following points:

1) The tariff values according to power supply-demand situation, time of the day, etc.
2) The optimum time scheduling of orange and green loads.
3) The highest reliability and stability of the grid.
4) Minimizing the probability of outage.
5) Fairness amongst customers.

Practically, all user loads require some time to complete tasks. Along with the demand, the prices also fluctuate over 24 hours. Hence, we optimize on a per-day basis by scheduling appliances, yet, meeting all customer preferences and technical limitations [20]-[23]. In actuality, the load demands fluctuate over months/seasons. However, this is not considered in our model. The time unit is Δ minutes. Therefore, the number of periods per day is given by

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$$N = \frac{1440}{\Delta} \tag{1}$$

The energy consumed per day is written as

$$E_t = \frac{\Delta}{60} \sum_{i=1}^{N} P(i) \tag{2}$$

where, $P(i)$ is the peak power in kW within a time period i. The total power at each time slot is expressed as

$$P(i) = \sum_{k=1}^{M} \left(\sum_{j=1}^{r_k} \eta_{kj}(i) R_{kj} + \sum_{j=1}^{o_k} \alpha_{kj}(i) O_{kj} + \sum_{j=1}^{g_k} \sigma_{kj}(i) G_{kj} \right) \tag{3}$$

where M is the total number of customers, r_k is the number of red loads of a customer k, $\eta_{kj}(i) \in \{0,1\}$ where $\{0,1\}$ is an indicator that the j^{th} red load of the k^{th} customer at the i^{th} period is either ON or OFF. R_{kj} is the rating power of the j^{th} red load. Similarly, o_k is the number of orange loads of a customer k, $\alpha_{kj}(i) \in \{0,1\}$ where $\{0,1\}$ is an indicator that the j^{th} orange load of the k^{th} customer at the i^{th} period is either ON or OFF. O_{kj} is the rating power of the j^{th} orange load. Also, g_k is the number of green loads of a customer k, $\sigma_{kj}(i) \in \{0,1\}$ and $\{0,1\}$ is an indicator that the j^{th} green load of the k^{th} customer at the i^{th} period is either ON or OFF. G_{kj} is the rating power of the j^{th} orange load.

It is possible to control the total power consumption with the switching parameters; $\eta_{kj}(i)$, $\alpha_{kj}(i)$ and $\sigma_{kj}(i)$ for red load, orange load and green load, on an item-by-item basis. However, it is assumed that $\eta_{kj}(i)$ is set by the customer not by the electric power supplier. Since red loads are not to be re-scheduled. For the orange loads, we have the following requirement

$$\sum_{i=1}^{N} = T_{kj} \tag{4}$$

where, T_{kj} is the total number of periods that the j^{th} orange load of the k^{th} customer should be connected per day. If we assume that a certain orange load should be connected for t_{kj} minutes, then:

$$T_{kj} = \left[\frac{t_{kj}}{\Delta} \right] \tag{5}$$

where, [x] returns the round-up integer of x.

Finally, green loads are the most flexible load that can be rescheduled. There are no constraints to be met with respect to green loads. Nevertheless, the power companies performance and reputation are in a way linked to ensuring less green loads rescheduling. In the system model, we have several constraints that should be achieved as:

- The maximum electricity bills that the customer will want to pay.
- Achieving good profit for the utility provider.
- Providing constant electricity supply to the red loads.
- Balancing the electricity supply-demand without geopadizing the grid stability.

The peak power demand is identified as

$$P_{peak} = \max_{\forall i=1,\ldots N} P(i) \tag{6}$$

In the next section, various mathematical optimization algorithms are presented to achieve different criteria.

III. Optimization Algorithms

Optimization in this context is a tool to find the optimum schedule of customer loads to achieve specific objectives and constraints. The objectives are usually set by the electric power suppliers. Scheduling schemes can vary greatly depending on the optimization criteria. Therefore, it is important for the electric power supplier to choose the right purpose and the right scheduling scheme. In this section, we present a variety of optimization algorithms and we show the scheduling impact. The total electricity bills for the k^{th} customer is related to

$$\mathrm{C}_k = \sum_{i=1}^{N} \Big[\sum_{j=1}^{r_k} \eta_{kj}(i) R_{kj} f(i) + \sum_{j=1}^{o_k} \alpha_{kj}(i) O_{kj} f(i) + \sum_{j=1}^{g_k} \sigma_{kj}(i) G_{kj} f(i) \Big]$$

where, $f(i)$ is the tariff at time period (i). It is normally large during the peak power demands and low during off-peak power demands. Hence, $f(i)$ is a dynamic parameter that depends on many factors such as the time, the power source, and the electric power supplier. In all the proceeding optimizations formula given next, we are looking for the optimums $\alpha_{kj}(i)$ and $\sigma_{kj}(i)$ which are either on 0 or 1. It is obvious that all the following optimization algorithms can be classified as one form of Knapsack problems, Knapsack problems are NP-complex problems as demonstrated in [10].

A. Optimization Formula 1: Minimizing Electricity Bills

Our criterion is to minimize the total electricity bills of the consumers while respecting the constraints; the optimization formula can be expressed as given in [7]

$$\min_{\alpha_{kj}(i), \sigma_{kj}(i)} \sum_{k=1}^{M} C_k \tag{7}$$

subject to

$$C_k \le C_k^{max} \forall k = 1, \ldots M; P_{peak} \le P_t^{max} \tag{8}$$

$$\sum_{i=1}^{N} \alpha_{kj}(i) = T_{kj} \forall k = 1, \ldots M; j = 1, \ldots, ok \tag{9}$$

The above optimization problem guarantees minimum electricity bills. Nevertheless, it has a serious limitation that green loads are not being served. The behavior of this algorithm is analyzed in simulation.

B. Optimization Formula 2: Maximizing Utility Performance

Utility performance is defined by the reliability, availability, and efficiency of the power supply while maximizing the utilitys revenue. This can be accomplished by the percentage of supporting the largest green loads. However, other restrictions must be observed, such as maximum allowable bills and maximum power supply. The optimization problem can be formulated as follows:

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$$\max_{\alpha_{kj}} \sum_{k=1}^{M} \sum_{i=1}^{N} \sum_{j=1}^{g_k} \sigma_{kj}(i) f(i) \quad (10)$$

subject to

$$C_k \leq C_k^{max} \forall k = 1, ...M; P_{peak} \leq P_t^{max} \quad (11)$$

$$\sum_{i=1}^{N} \alpha_{kj}(i) = T_{kj} \forall k = 1, ...M; j = 1, ..., ok \quad (12)$$

The problem with this optimization is that it does not guarantee fairness amongst customers in terms of the green loads.

C. Optimization Formula 3: Fairness in Scheduling Appliances

The utility performance could be measured by the percentage of supporting green loads. Nonetheless, other constraints such as the maximum allowed bills and the maximum power supply should be achieved. The optimization problem could be formulated in the following manner:

$$\max_{\alpha_{kj}(i)\sigma_{kj}(i)} \prod_{k=1}^{M} \left(\sum_{i=1}^{N} \sum_{j=1}^{g_k} \sigma k_j(i) \right) \quad (13)$$

subject to

$$C_k \leq C_k^{max} \forall k = 1, ...M; P_{peak} \leq P_t^{max} \quad (14)$$

$$\sum_{i=1}^{N} \alpha_{kj}(i) = T_{kj} \forall k = 1, ...M; j = 1, ..., ok \quad (15)$$

Since the product of the consumers green loads have been used. This optimization algorithm will lead to fairer distribution amongst consumers. Maximizing this leads to a fairer allocation of power to the green loads.

IV. Performance Analysis

The performance analysis is carried out with simulations. In the simulation set up, for the purposes of analysis, there are 20 fixed customers and each customer has six red loads. The red loads are determined by the customer and are not included in any load schedules. Also, each customer has four orange loads and three green loads. The loads with the rated power are exhibited in Table I. The orange and green loads have an ON-OFF schedule permitting by the PMS. However, each load has an average number of being ON per day and also the average time duration to be achieved. The number of being ON follows a Poisson distribution and the time duration is a random process with an exponential distribution [8]. We divide a day into 288 periods, with the length of each period been 5 minutes. On the load side, we consider dynamic load represented by EVs. The dynamic loads are connected randomly at a Poissonian rate to the power network and consume 10kW. The details of the power sources are as follows:

- Macrogrid supply with normalized tariff at \$0.09/kW between 7:00 - 18:00 and \$0.05/kW between 18:00 - 7:00 (i.e. bi-tariff). The maximum power per day is 500kW.
- Renewable (solar, wind, storage battery, photovoltaic, etc.) supply with uniform random power from 50kW to 100kW, with maximum energy per day as 500kW.
- Storage energy supply with power up to 200kW, but with total energy per day of 500kW and at \$0.09/kW all day. (fixed tariff).

For verification purposes, we analyzed the use of home appliances by customers at a fixed rate during the day and another fixed-rate at night. This is known as the bi-tariff. The said tariff is fixed at \$0.09 at day and \$0.05 at night and the supply power is sourced from a non-RES source.

TABLE I
THE POWER PROFILE OF THE CONSIDERED APPLIANCES

Appliances	Power rating (Watts)	Type	Time (minutes)
Electric cooker	200	Red	As needed
Television	120	Red	As needed
Fridge	400	Red	As needed
Security lamps	100	Red	As needed
Computer	200	Red	As needed
Electric iron	500	Orange	60 minutes
Dish washer	2000	Orange	45 minutes
Sew. machine	80	Orange	As needed
Vacuum cleaner	650	Orange	45 minutes
Water pump	750	Green	90 minutes
Heater	700	Green	120 minutes
Water heater	450	Green	As needed

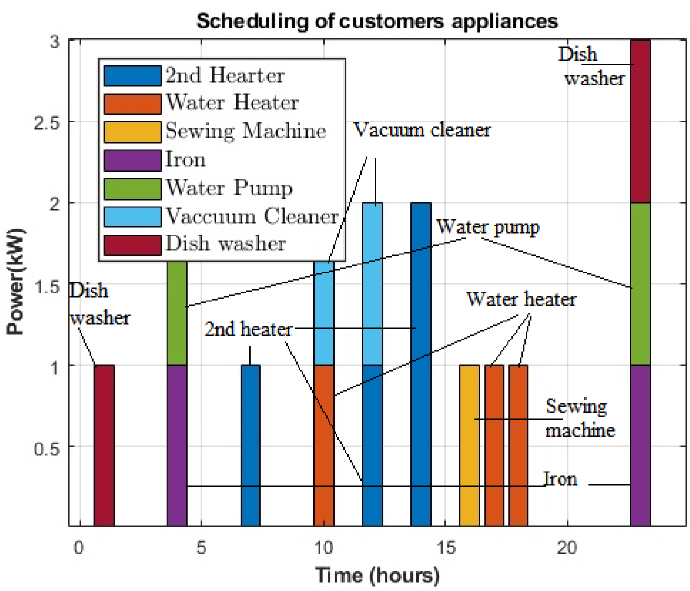

Fig. 3. Scheduling Customer Appliance based on Hourly Fluctuating Tariff.

This reflects the practical situation as electricity tariff is usually higher at peak load periods and lower at off-peak periods. Simulation results show that the optimal objective value for scheduling the appliances using the MILP is \$19.45. This shows a significant reduction of the electricity bills compared to the electricity bills of \$22.45 without scheduling.

Using the hourly fluctuating tariff, where the said tariff fluctuates between \$0.05 and \$0.09. The optimal objective value of \$17.34 is achieved showing gross decrement in the electricity bills compared to the bills without scheduling.

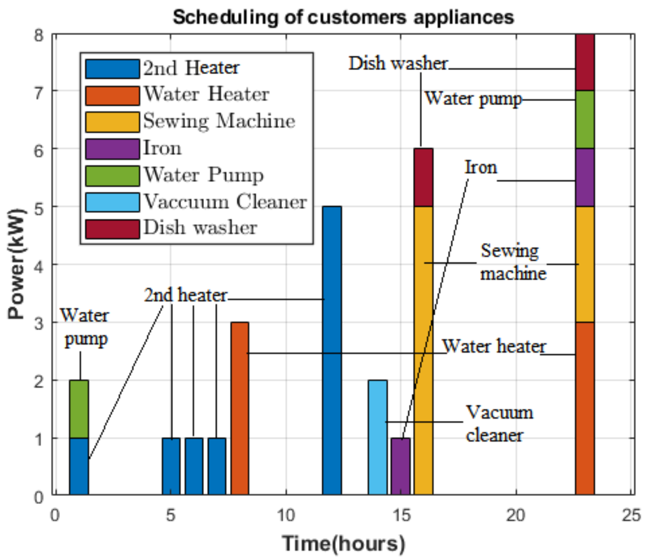

Fig. 4. Scheduling Customer Appliance based on Bi-tariff.

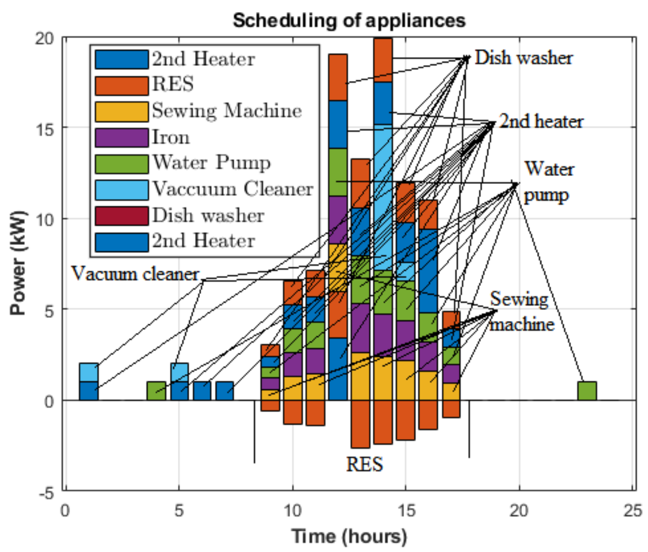

Fig. 5. Scheduling Customer Appliances with RES based on Hourly Fluctuating Tariff.

Again, with power from a RES and simulated based on the parameters given under the performance analysis in Table I, using the bi-tariff mentioned. The optimum value is obtained at \$20.48. The graph is as shown in figure 5. The graph of scheduling the appliances based on the hourly fluctuation tariff is shown in fig 6. Simulation results determined the optimal value at C19.45 showing decrement in the electricity bills compared to the electricity bills of C22.45 without scheduling. It is evident also in the simulation results that, the green loads ON-OFF (0-1) constraints are met.

V. Conclusion

We analyzed the problem of scheduling customers load for DR program in SG using a centralized MILP optimization algorithm. We deduced approximate expressions to minimize electricity bills, maximize utility performance, and ensure fairness in customers load scheduling. The primary novelty is that our proposed PMS supports customers desire load consumption patterns, yet, reduces electricity bills. Another

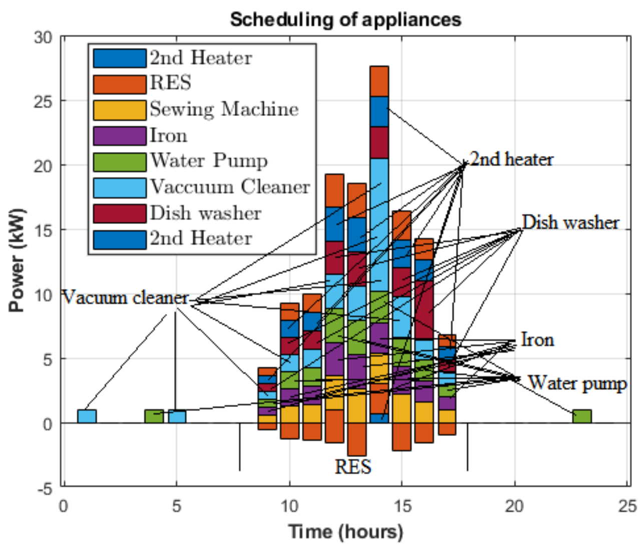

Fig. 6. Scheduling Customer Appliances with RES based on Bi-tariff.

novelty is that the proposed model guarantees fairness within the schedulable loads which is demonstrated by the extensive computational experiments.

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