Scheduling Smart Loads in Modern Buildings based on Metaheuristic Optimization

Mohammed Hijjo and Georg Frey
Chair of Automation and Energy Systems, Saarland University, 66123 Saarbrücken, Germany

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Abstract: Load scheduling is one of the most promising trends in smart grids. It enables renewable energy to be efficiently utilized and accommodated in the smart buildings. In this work, we propose a comprehensive scheduling approach of a group of non-preemptive loads in a 'greedy' manner in order to reduce the deficit between the aggregate scheduled load and the available low-cost generation and therefore, the levelized cost of energy (LCoE) can be minimized. In order to reduce the massive searching space and attain a good schedule within a reasonable time, an efficient metaheuristic optimization framework is proposed and implemented based on genetic algorithms. An illustrative example is used to carry out this work using artificially created loads representing different facilities inside a building complex.

1 INTRODUCTION

Recently developed technologies in smart grid sector, including smart loads and smart metering, have enabled a highly efficient prediction and identification of the electricity consumption of a facility in a smart building. Besides, the numerous adoption of renewable energy sources (RES) to replace fossil fuel generation, both together, provide the opportunity to maximize the efficiency of the system by good coordination of the existing power assets and loads in order to reduce the net gap between the demand and the low-cost energy offered by RES generation and the utility grid in the off-peak times.

Until recently, various approaches have been proposed and applied to coordinate the generation sources in order to meet the varying demand while keeping the electricity cost at optimal levels (Zhu, 2009). However, due to ever increasing demand and motivated by the affordable prices of the renewable-energy based systems, a growing desire exists to control or optimize the demand growth in order to facilitate the integration of RES into domestic and industrial sectors.

Yet, the fluctuating nature and intermittency of the RES are the still forming a barrier against entirely relying on them as a main power provider or even increasing their penetration level in generation side. In spite of that, this obstacle can be overcome by using a proper energy storage to stabilize the operation and compensate the shortage (Pickard et al., 2012). This solution is not always affordable, especially in standalone and remote systems, or in buildings subject to severe power outages, where the fluctuating supply cannot be matched by a greater energy storage on all occasions. Otherwise, this will simply add cost and complexity to the system.

A potential alternative solution will be influencing the load demand, totally or partially, in order to lower the need for larger energy reserve. A proper scheduling of some shiftable loads can improve the reliability of power delivery for customers during (macro)grid blackouts or emergency islanded operation. Once the system is integrated with some smart loads, that can be scheduled in advance, an efficient algorithm could be developed to reallocate these loads in another time, in which, the total energy cost can be minimized and the utilization of RES can be maximized as well.

The need for some controllability over load is not only to assist in accommodating more RES into different power systems around the world, but also there is an important and persistent need to develop and apply such a solution in countries which have weak power systems or suffer from continuously interruption of the utility grid. Especially in developing countries, a large number of buildings

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including healthcare facilities, schools and small businesses are suffering from a serious lack of a continuous and stable power supply. This issue has forced the decision makers and the engineers to develop some urgent solutions to meet the ever increasing demand, usually depending on diesel generators, which are costly and environmentally unfriendly too. The reason behind not using such logical approach previously, is the need for efficient load forecasting techniques that can predict the upcoming load accurately.

1.1 Related Works

A huge work has been done in the context of load scheduling. A heuristic algorithm to schedule a group of smart appliances in a smart building subject to a real-time pricing has been proposed by (Lee et al., 2013). Another work has been conducted on a smart building environment but using a set of household appliances that allow for a limited interruption time (Caprino et al., 2015). A heuristic-based load shifting optimization approach has been proposed by (Logenthiran et al., 2012), where three adjacent power networks have been chosen to carry out the study.

Another load scheduling algorithm based on game theory has been proposed by (Mohsenian-Rad et al., 2010). The main objective was to optimize the energy costs by reducing the aggregate peak-to-average ratio of the total energy demand, while respecting the privacy of the customers.

Considering the previously listed literature review and the other ongoing work in this domain; e.g. (Habib et al., 2016), (Manic et al. 2016), and (O'Brien el al., 2016), it has been realized that the number of studies that have discussed the problem of scheduling dynamic non-preemptive loads from the perspective of smart grids and smart buildings are very few. Two reasons maybe behind that, which are: the complexity of solving such a load scheduling problem, which is agreed upon to be a NP-hard problem (Baruah et al., 2004), and the difficulties involved in modelling such continuously-operating loads with a non-fixed power consumption.

1.2 Scope of Work

This work takes care of the load scheduling in smart building as an important function of the tertiary level in controlling future microgrids. Thus, the scope of this work does not include the voltage stability or power quality at the point of common coupling (PCC). However, it tackles the uppermost control level, which has the longest discrete time steps; e.g. ranging from intra-hours to intra-days. To this end, this work offers a proactive scheduling plan for the smart loads which announce their desired operation pattern or the associated consumption profiles in advance; e.g. a day ahead. In other words, the proposed algorithm will attempt to reallocate the aggregated loads to closely follow the low-price available power; e.g. from utility grid or local RES generation. The load profiles are known in advanced, but they should be reallocated in better time span in order to minimize the total energy cost.

Furthermore, the proposed approach will be conducted on a deterministic system, where all load profiles and RES generation as well as the off-peak hours of the utility grid are known in advance. This assumption provides the 'best case' scenario for a stochastic system where the generation/demand profiles are not precisely known ahead of time. Later on the solution will be extended to include tackle the uncertainty of the load as well as the RES generation. Detailed description will be presented in the following sections.

2 PROBLEM FORMULATION

Suppose that a part of a building complex consists of several smart loads that declare their consumption for the next day on the day ahead. These smart loads, under this definition, can be called *notified*, where the corresponding load profiles are known in advance within a narrow margin of error. The load profile per each is defined over $\boldsymbol{T}$ time slots representing the schedule period (here is one day). A time slot is chosen in consistence with the data rate of the connected devices and the smart metering system, which is usually taken as 10, 15, 30 or 60 minutes.

A non-empty set $\boldsymbol{S}$ consists of $\boldsymbol{N}$ smart shiftable loads is assumed, $\boldsymbol{S} = \{\ell : \ell \in \mathbb{N}\}$, where $\mathbb{N}$ is the set of the natural numbers, e.g. positive integers greater zero. Each single load ℓ has a deterministic load profile $P_\ell(t)$ announced in advance in accordance with the planned operation of the next day.

The total unscheduled load profile of these shiftable loads can be mathematically formulated as given below in Equ. 1

$$S(t) = \sum_{\ell=1}^{N} P_\ell(t) \qquad 1 \le t \le T \qquad (1)$$

2.1 Smart Shiftable Load

A smart load can be a single appliance or a cluster of devices operate in a particular way to perform a certain function in one of the facilities inside the whole system. The corresponding load profile of each load is predetermined, as it is smart, and the preferred operation time is predefined too. However, as illustrated in Figure 1, the activation time must be commanded by the system operator (*active mode*).

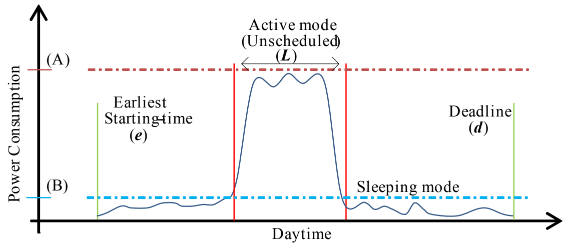

Figure 1: Example load profile of a smart shiftable load.

Several examples can be given for such smart loads in different sectors, for instance, washing machines and dryers in residential sector can be considered as smart loads. Heating, ventilation, and air conditioning (HVAC) systems are a good example for smart loads in the commercial and industrial sector, and they have been used as a load service for large scale of buildings (Lu, 2012). In the healthcare facilities, different loads and plants can be good candidates for performing load scheduling, such as: laundry, sterilization unit, and waste disposal unit. All of these facilities, generally, can be considered as 'stand-alone' plants or loads and their load profile can be efficiently forecasted depending on the different operation circumstances.

Ideally, a shiftable load ℓ is modelled by a quadruple: (e_ℓ, d_ℓ, L_ℓ, A_ℓ), where e_ℓ, d_ℓ, L_ℓ, and A_ℓ are the earliest possible starting time, the deadline, the duration of the active mode, and the load level during the active mode respectively.

In this work, an advanced version of this model is introduced, in which, the load can have multiple modes of operation that feature the individual functionalities associated with each smart load. Thus, the resulting model will be modelled as a quintuple. Specifically, the added element B_ℓ represents a nother mode of operation, e.g., sleeping mode, in which, the load consumes a much less power than usual to be ready for the normal operation upon request. Furthermore, the stochastic nature of the each individual load is modelled using some statistical properties added to each mode of operation.

Three exemplary loads are defined in Table 1 and illustrated as shown in Figure 2, showing different timings and power consumptions as well as highlighting two modes of operation with their means and standard deviations.

Table 1: Three exemplary shiftable smart loads.

Load	Tuples (*units*)				
	e_ℓ (*time*)	d_ℓ (*time*)	L_ℓ (*time*)	$A_\ell\,(\mu,\sigma)$ (*power*)	$B_\ell\,(\mu,\sigma)$ (*power*)
ℓ_1	2	12	6	(135, 8)	(15, 5)
ℓ_2	4	11	3	(220, 5)	(20, 10)
ℓ_3	7	15	5	(60, 10)	(0, 0)

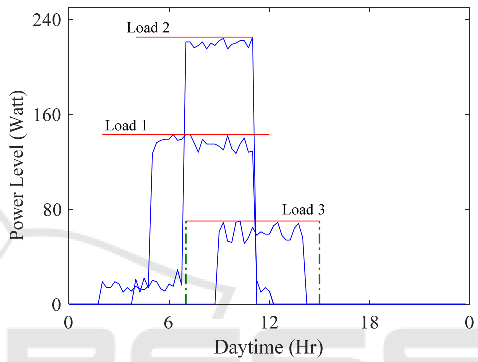

Figure 2: Illustrative profiles of three smart loads.

Obviously, the presented loads here have two modes of operation. However, the sleeping mode of the third load is adjust to zero.

Here, the proposed algorithm is dedicated to provide the operator with the optimal execution time of each of these loads in order to minimize the LCoE and maximize the net utilization of the local RES generation. To this end, the permissible operation interval ϑ_ℓ of each load ℓ should be declared in advance, in which, the active mode period must be accomplished. See Equ. (2):

$$\vartheta_\ell = [e_\ell, d_\ell] \tag{2}$$

Under this definition, the latest activation time a_ℓ is given by Equ. (3):

$$a_\ell = d_\ell - L_\ell \tag{3}$$

Thus, a mapping function should be defined in order to shift the load in accordance with the aforementioned parameters. A typical mapping function κ may bring the selected load τ time-slots forward or backward, as defined in Equ. (4):

$$P_\ell \xrightarrow{\kappa} \tilde{P}_\ell = \kappa(P_\ell) = P_\ell[t - \tau_\ell] \tag{4}$$

As the proposed algorithm is *offline* and deals with a *notified* system, the value of the shifting index can be positive or negative. However, in real-time systems, in order to fulfill the causal consistency condition, the shifting index $\boldsymbol{\tau}$ associated with a scheduling operator ĸ is chosen to be positive integer.

2.2 Low-Price Power Signal

The low-price power signal has an important role in solving this problem, where it must be tracked as closely as possible. In isolated systems, which is powered solely by renewables, this signal results from the RES-power alone. On the other side, in grid-connected systems, it can result from both; the renewable generation and the incentive off-peak periods of the utility grid, where the power price is negligible, as compared with peaking times. In modern power systems, this signal can be *notified* in advanced as an incentive for customers to schedule a part of their consumption accordingly.

In this work, it is assumed that the utility grid adopts a two-level power price, in which, the off-peak times follow a lower fixed price c_l and the counterpart peaking times follow a higher price c_h as given in Equ. (5):

$$U_g(t) = \begin{cases} c_h, & t \in [t_1, t_2] \\ c_l, & otherwise \end{cases} \tag{5}$$

The low-price signal $\Upsilon(t)$ is represented by the total sum of the solar generated power from the installed array over the building and the utility grid capacity during off-peak, $t \in [t_1, t_2]$, see Figure 5.

The target is therefore to accumulate the greatest possible amount of these loads in these time spans without overriding the capacity limit of the main power feeder.

2.3 Optimization Algorithm

In order to find the optimal scheduling operator ĸ associated with each smart load in the system, we chose here to penalize the absolute-value norm of the error between the low-price power signal and the aggregate scheduled load profiles as formulated in Equ. (6):

$$G(t) = \left\| \Upsilon(t) - \left(\sum_{\ell=1}^{N} P_\ell[t - \tau_\ell] \right) \right\| \tag{6}$$

Where $\Upsilon(t)$ is the low-price power signal and $P_\ell[t - \tau_\ell]$ is the shifted version of the smart load ℓ corresponding to the scheduling operator ĸ. The general overview of the proposed offline load scheduling scheme is shown in Figure 3.

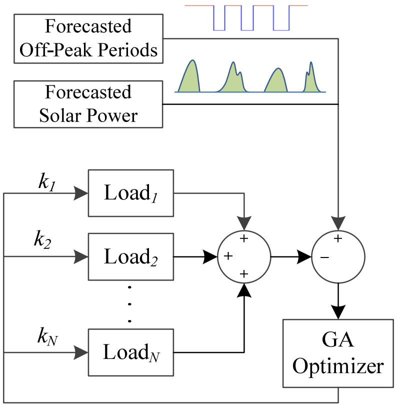

Figure 3: General overview of the proposed load scheduling system.

The main idea is that to maximize the autocorrelation between the low-price signal and the aggregate load subject to the permissible activation time of each load. It is important here to distinguish between this problem and other classical constraint-based scheduling problems (Wall, 1996), where the tasks, i.e. the loads, are constant and require a certain share of the resource. However, the dynamic nature of the loads here makes it even harder to solve the problem without using relaxation techniques to eliminate the effect of the fluctuating demand. As presented in Figure 3, the proposed scheduling approach targets to reallocate the different loads to minimize the difference between *announced* low-price power profile and the aggregate scheduled loads, so as to increase the benefit from the available low-price power as much as possible. The existing scheduling problem is a complicated optimization problem, which is NP-hard (Baruah et al., 2004). Therefore, finding an optimal schedule for a huge set of schedulable loads is very complicated problem and thus, the exact solution might be hard to find without enumerating all possible schedules and then evaluating them.

To elaborate on this issue, if we have a set of $\boldsymbol{N}$ loads with at least $\boldsymbol{M}$ possible positions for each load to start the active operation, the complexity of the searching space will be $M^{\boldsymbol{N}}$. Obviously, the complexity of the problem is exponentially increasing with the number of loads and/or the possible schedules of each load. In order to cut down the computation time, the developed optimization approach applies the Genetic Algorithms to handle this problem (Mitchell, 1996).

The genetic-based approach belongs to the bigger class of evolutionary algorithms (EA), which is one of the metaheuristic stochastic optimization techniques that can provide a solution to an optimization problem with less computational effort than iterative ones. Compared to conventional algorithms, metaheuristics sample a set of solutions which is too large to be completely sampled. Thus, by searching over a large set of feasible solutions, metaheuristics can often find good solutions with less computational effort than optimization algorithms, iterative methods, or simple heuristics (Blum et al., 2003).

A group of initial schedules are randomly generated at the beginning. Some of the feasible schedules are selected and then merged as a one schedule by the crossover and mutation operations, and then the schedule set is evolved by replacing a schedule in the old set by the newly generated schedule. This process is repeated until the schedule set converges (Lee et al., 2013).

An abstract pseudo-code of the applied GAs is given below in Figure 4.

```
1.Inputs
Load profiles, Possible schedules , Off-peak
periods, PV generation.
2.Initialization:
randomly seeded schedules.
3.Cost function evaluation (Equ. 6)
4.Selection:
Select the best candidate solution among the
present generation before step in the next
generation.
5.Crossover and mutation:
The new possible candidate solution is
generated from the parents which survived.
6.Evaluate the cost control function
again (STEP 4)
7.Termination:
After exceeding the time budget or generation
limit or satisfying the minimum criteria.
8.Output:
The values correspond to the best/final
solution.
```

Figure 4: Pseudo-code of the GA-optimization algorithm.

3 NUMERICAL EXAMPLE

A preliminary simulation is conducted using a clinical facility building incorporating a group of six shiftable loads. The low-price power signal is generated from the aggregation of the off-peak period from the utility grid in Gaza-city and the onsite solar generation. Other essential loads are assigned to be supplied using the conventional generation as they need a continuous and stable supply without any interruption. The building is mainly supplied from the utility grid, which has a feeder capacity of 18 kW. In spite of the low-price power, the grid is interrupting on a daily basis, which makes relying solely on it impossible. Therefore, the building was fitted recently with a 20kW$_p$ solar array to assist the legacy standby diesel generator.

The used diesel generator has a capacity of 20 kW and its associated fuel cost is modelled by fitting the manufacturer data (Diesel Service, 1981). The grid price is considered c_l = 0.16 \$/kWh during off-peak hours and the price associated with diesel operation under the rated load is c_h = 0.56 \$/kWh. Half of the grid capacity is reserved for essential loads and the second half is assigned for the shiftable loads.

The off-peak signal and the available PV generation over a four-days are shown below in figure 5.

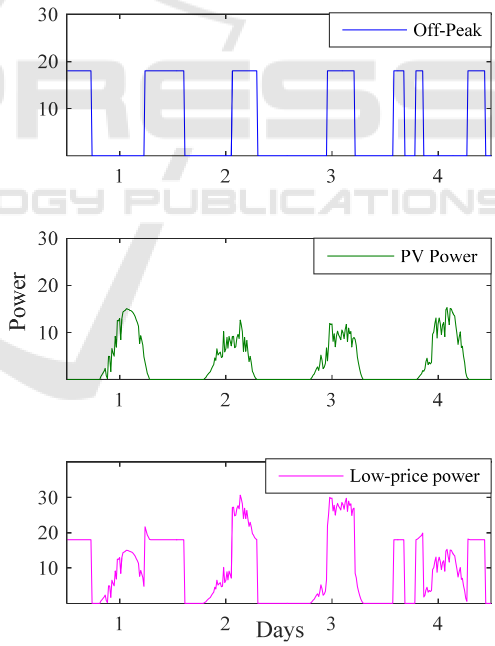

Figure 5: Sample 4-days off-peak and PV generation.

The system is modeled using MATLAB and the optimization algorithm is conducted using the provided optimization toolbox.

The optimization window is considered here as a single day and then the optimization process should be repeated in accordance with the new timing constraints for the day after. The convergence of the optimization process for one sample day is depicted in figure 6, where the searching process is converged after about 100 generation, and then the improvement rate is almost negligible. The resulting value here (approx. 820) represents the penalized absolute-value norm of the error between the low-price power signal and the aggregate scheduled load profiles as formulated in Equ. (6).

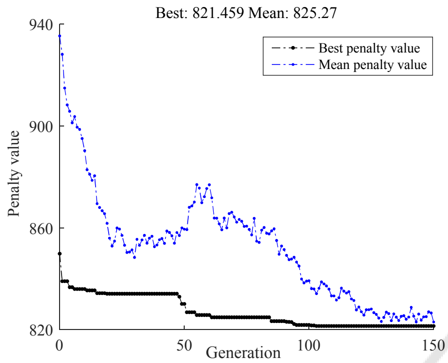

Figure 6: Convergence of the proposed GA-Scheduling.

The activation times of five sample loads are expressed in figure 7, showing the original operation and the proposed activation during the first day.

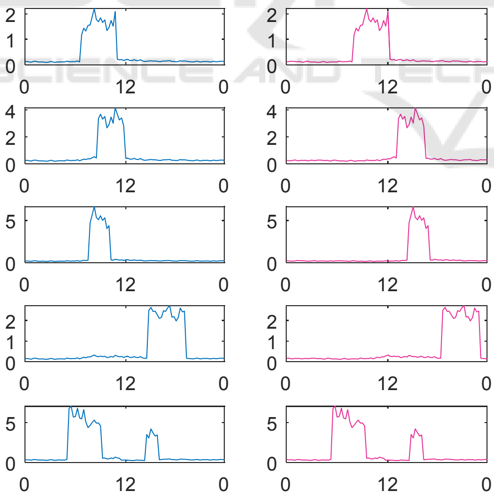

Figure 7: Scheduling results of three sample loads.

Figure 8 shows the final results over a four-days simulation window. It presents the aggregated low-price power (green), i.e. which has to be tracked as well as the total loads before performing the scheduling (dotted red) and finally, the total loads after performing the scheduling (blue).

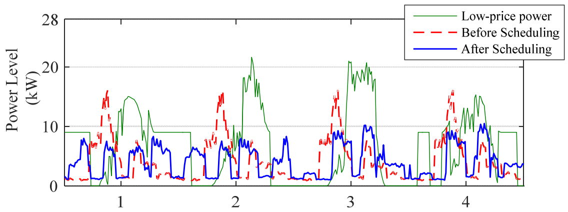

Figure 8: Scheduling results over four-days simulation.

Figure 9 illustrates the instantaneous energy cost before (red) and after (blue) performing the proposed scheduling algorithm.

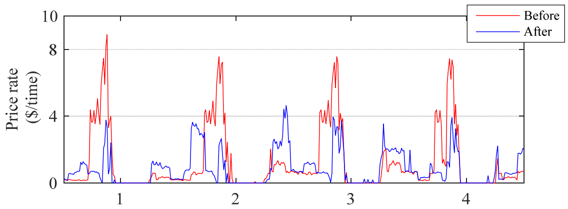

Figure 9: Instantaneous end-price of energy.

Some performance indices and end results are calculated and concluded in Table 2, presenting the net utilization factor of the solar power and LCoE as well.

Table 2: Performance indices.

Performance index	Before scheduling	After scheduling
Total PV production (kWh)	323.48	
Aggregate Shiftable Loads (kWh)	388.63	
Net PV usage (kWh)	146.54	180.38
Total supply cost ($)	117.6	82.13
PV Utilization Factor (%)	45.3	55.76
LCoE ($/kW)	0.30	0.21

4 DISCUSSION

Unlike other works, such as (Habib et al., 2016), and (Leithon et al., 2017), where preemptive loads have been used to reshape the aggregate load, e.g. that is they can be supplied with interruptions, the proposed work here aims at reallocating each shiftable load to another time interval instead of reshaping them so that the resulting consumed energy after scheduling is similar to their unscheduled counterpart. The reason behind that is to avoid the so-called "*rebound effect*", because simply switching the loads ON and OFF will not lead to the same desired performance if they work continuously as usual. In such cases, energy is naturally not saved and expectedly another peak will be generated (Palensky et al., 2011).

Additionally, it is important here to highlight the difference between the addressed model in this work and other classical models (Ali et al., 2012) that use 4-tuples only expressing the timing constraints and a constant power demand over a single mode of operation, which makes the problem somehow similar to constraint-based problems (Wall, 1996). Unlikely, the presented model here expresses the fluctuating nature of the load that can have multiple operation modes with some variability on the power consumption.

Another practical aspect is the scheduling window, which is taken here as a single day and then the algorithm is repeated for the next day using the new data. In this regards, one load cannot be requested more than once within the same window. Otherwise, two or more identical loads with different activation constraints should be used in order not to allow any overlapping of the operation of same load in that facility.

Formerly, the developed scheduling algorithms were adopting some scheduling policies used in real-time processing such as Earliest Deadline First (EDF) and Least Laxity First (LLF) which assign the tasks, e.g. loads, according to their deadlines or the slack times (Subramanian et al., 2012). However, in renewable energy systems with versatile loads, such algorithms still need an accurate forecasting tools and systems to handle the fluctuating nature of the RES and the dynamic price of the grid.

Therefore, the matter of prioritizing loads should consider both: timings of the loads and their consumption level at each time slot. Obviously, the dominants loads will be those with higher consumption and less timing flexibility than others, which will diminish the effect of other shiftable loads but with lower consumption.

5 CONCLUSION AND OUTLOOK

An easy-to-implement load scheduling approach based on the *notified* nature of the system was proposed. Besides, a straightforward model for smart shiftable loads was introduced in this work. The proposed approach has adopted the GAs to cut-down the searching space and find the optimal schedule within a reasonable time budget.

There are three important topics that have not been explored in this paper, and will be the subject of our future publications:

(a) Reduction the capacity of the conventional generation, e.g. diesel generator. The economic basis for this issue should be clearly justified through synthetic examples and much more comprehensive simulations using real data.
(b) The incorporated energy management scheme, which will highlight the power routing between all system components, including the static and the essential loads which cannot be shifted in time.
(c) Online adaptation of the resulting schedules using shorter time window instead of performing the algorithm once per day. Thus, the improvement rate can be further increased according to the recent measurements of the RES generation and the loads as well.

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