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Iterative learning for optimal residential load scheduling in smart grid

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A B S T R A C T

In this paper, as a fundamental problem in smart grid, the residential load scheduling is studied in a comprehensive way. The main contributions lie in threefold. First, three indices, i.e., the power consumption expense, the robustness of schedule subject to uncertain electricity price and the satisfaction of customer, are taken into full consideration. We propose to optimize simultaneously the three indices via convex optimization. Second, iterative learning is utilized to setting parameters in the objective function, and keeps a proper tradeoff between the consumption expense and the satisfaction index. Third, in order to fully characterize the operation states of appliances, both binary and continuous variables are used, which results in a hybrid mixed-integer quadratic optimization problem. The relaxation technique is utilized to tackle the hybrid optimization problem. Theoretical analysis of the performance gap based on the proposed approach is provided as well. The performance of the proposed approach is illustrated by simulations. The parameter settings reflect actual preference and consumption manner of the consumer. In addition, both peak-to-average ratio of power load and variation of power load are reduced.

1. Introduction

The smart grid is widely deemed as the next generation grid [1–4]. Benefitting from smart grid technology, the reliability, stability and efficiency of power grid are significantly enhanced [5–8]. Demand Response Management (DRM) is one of the main features in smart grid, which is implemented by system operators and customers to reduce peak-to-average ratio of demand, and hence improves efficiency and reliability of the power grid [9–12]. Residential load scheduling is an essential problem in DRM research. In a lot of studies, the residential load scheduling problem is addressed by the means of real time pricing (RTP), power consumption expense, satisfaction of customer and price prediction [13–17].

Power consumption expense minimization is one of the most important goals of residential load scheduling, which is strongly related to the real time pricing [14,18–24]. The work in [14] proposes task scheduling policies to minimize consumers' electricity payment. In [18], the authors propose an appliance commitment algorithm based on price and consumption prediction to meet objective such as minimum payment.

Additionally, satisfaction of consumer is also considered with residential load scheduling. Satisfaction of consumer is strongly related to the consumption habit of the consumer [13,25–28]. Actually, there is a tradeoff between power consumption expense and satisfaction of consumer. In [13], the authors propose an analytical framework to achieve a desired tradeoff between minimizing electricity payment and minimizing the waiting time of appliance

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tasks with prediction of RTP. Similarly, the work in [25] aims at minimizing the electricity provider cost plus the total user dissatisfaction with lost messages.

Prediction approaches of RTP are utilized in residential load scheduling [13,18]. Due to the uncertainty of the renewable energy and unknown response of users, it is really difficult to precisely predict the RTP [29,30]. The prediction error can be reduced to 13% average, which is still cannot be ignored [13]. However, robustness subject to price uncertainty is not well considered in the previous paper [13,18,30].

Most of the previous works mentioned the concept of satisfaction. Especially, the total cost of waiting across all appliances in [13] and the total dissatisfaction of the end-users in [25] are proposed to evaluate the satisfaction level of the consumer. However, the parameters are predetermined before implementing the schedule algorithm. That is to say, the tradeoff between expense and satisfaction level may not be well studied. Actually, the satisfaction level reflects the priorities of the consumers. Thus consumers should participate in the parameter settings in the objective function.

The tradeoff between the expense and satisfaction index is needed to be well studied. In addition, the previous studies partially address residential load scheduling with price uncertainty or customer satisfaction. A full consideration with power consumption expense, the robustness and customer satisfaction is needed when studying the residential load scheduling.

There are three main contributions in our paper.

1. Three indices, i.e., the power consumption expense, the robustness of schedule subject to uncertain electricity price and the satisfaction index of the customers, are taken into full consideration in scheduling. It is formulated as a constrained multi-objective optimization problem, which can be effectively solved via convex optimization.
2. We use iterative learning to obtain the consumption habit, i.e., the tradeoff parameter between the consumption expense, and the satisfaction index and the target load of all appliances. In addition, we prove that the tradeoff parameter will converge to a fixed value.
3. In order to fully characterize the operation states of appliances, both binary and continuous variables are used in scheduling, which results in a hybrid optimization problem. Then, the linear programming relaxation techniques are utilized to tackle the hybrid optimization problem. Theoretical analysis of the performance gap based on the proposed approach is provided, as well.

The remainder of this paper is organized as follows: Section 2 describes the system models associated with load scheduling. In Section 3, residential load schedule problem is formulated as a constrained multi-objective optimization problem. In Section 4, interior-point method and linear programming relaxation techniques are presented to solve the problem. We propose a novel iterative learning method to obtain the tradeoff parameter and the target load of all appliances in Section 5. Numerical results are illustrated in Section 6. Finally, we draw conclusions in Section 7.

2. System model

Consider a residential consumer involving in DRM scheme in the smart grid with appliance set $\mathcal{A}$.[1] The number of appliances $N \triangleq |\mathcal{A}|$. One day cycle is divided into a time slot set $\mathcal{H}$, with the number of time slots $H \triangleq |\mathcal{H}|$. The consumer is equipped with a smart meter, which predicts the RTP and to determine the operation condition of each appliance. In summary, the notations used in this paper have been listed in Table 1.

2.1. Price uncertainty

With equipment of smart meters, real-time price prediction can be realized one day ahead. However, no matter how precise the prediction results are, there still exists prediction error, which can be regarded as an uncertainty.

Without loss of generality, we assume that p^h is independent and identically distributed random variable, i.e., i.i.d random variable [31]. The RTP in one time slot h is a random variable with mean p^h_{avg} and variance $(p^h_{unc})^2$, i.e., p^h_{avg} also refers to the predicted price at time h.

2.2. Consumer load scheduling

In general, home appliances of consumers can be categorized into two types: non-shiftable appliances (e.g., lighting, stoves) and shiftable appliances (e.g., PHEV, clothes washer). For each appliance $a \in \mathcal{A}$, we have an power consumption scheduling vector $\mathbf{x}_a$ with the following constraints.

Consumption constraint [13]: for each appliance $a \in \mathcal{A}$ at each $h \in \mathcal{H}$, there exist energy consumption constraints as follows:

$$\gamma^h_{a,\min} \le x^h_a \le \gamma^h_{a,\max} \tag{1}$$

However, for some tasks finished by certain appliances, the load amount can only be selected either $\gamma^h_{a,\min}$ or $\gamma^h_{a,\max}$, which correspond to the “of” condition and “on” condition, respectively. That is to say, hourly load of such appliances is actually binary variable. Similarly, for appliance a at time slot h, let y^h_a denote the corresponding binary variable. When the appliance a is “on”, $y^h_a = 1$. Otherwise, $y^h_a = 0$. Therefore the capacity constraint (25) can be described as

$$x^h_a = y^h_a \gamma^h_{a,\max} + (1 - y^h_a)\gamma^h_{a,\min} \tag{2}$$

Time coupled constraint [13]: which limits the power consumption x^h_a across each $h \in \mathcal{H}$

$$\sum_{h=1}^{H} x^h_a = E_a \tag{3}$$

The total power consumption of each appliance is a constant value which ensures that the appliance can finish the certain tasks in one day.

[1] For ease of presentation, we use consumer instead of residential consumer throughout this paper.