Appliance Type Constraint Design for Demand Response Smart Grid Systems

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Abstract— Recently, demand response (DR) technology applied with smart grid have studied as a method to minimize peak load and power loss. Many studies have used optimization tools to reduce peak load and to satisfy preferences and requirements of actual users. However, these studies did not focus on representing various types of appliance behaviors. In this paper, we study potent types of appliances to represent them as constraints for optimization problems in demand response scheduling smart grid systems.

Keywords— Smart Grid; Demand Response; Optimization

I. Introduction

Smart grid is actively researched to increase efficiency of energy production and consumption [1]-[5]. In particular, DR techniques can reduce peak load and power loss.

Real-time pricing with DR model sets high price for peak times and sets relatively low price for other times to reduce peak load [6]-[8]. Consequently, residential appliances are scheduled to operate in low-price hours to reduce electricity bills [5]. However, appliances have rules or desired time to operate because of their purposes or user preferences. Recent studies use optimization tools both to reduce electricity bills and to satisfy those kinds of requirements.

Studies using optimization tools formulate optimization problems to minimize electricity bills and evaluate requirement factors by electricity bills, so they can balance between them. In this case, appliance schedules are represented as variables and their operation rules are represented as constraints. The objective function of the minimization problem is calculated with these variables and constraints, resulting optimized appliance schedules. However, these studies focus on minimizing electricity bills in constrained problems, not focusing on representing the operation types of appliances.

In this paper, we focus on representing the operation types of appliances as constraints in optimization problems. First, we suppose operation types of appliances. Second, we propose type-constraint conversion methods for those operation types. Third, we propose combination rules for conversion methods.

II. Symbol Definition

Before discussing the operation types of appliances, we define symbols used in optimization problems. Suppose that we have N appliances to be scheduled in T timeslots. Let a^n be the nth appliance, $\boldsymbol{t} = \{t_1, t_2, \dots, t_T\}$ be the vector containing each timeslot and $\boldsymbol{s}^n = \{s_1^n, s_2^n, \dots, s_T^n\}$ be the schedule vector of nth appliance. Each schedule s_t^n is a 0-1 variable for nth appliance at timeslot t. If $s_t^n = 1$, the appliance is scheduled to operate at timeslot t and if $s_t^n = 0$ then the appliance is scheduled not to operate at timeslot t. Lastly, let $\boldsymbol{d} = \{d^1, d^2, \dots, d^N\}$ be the vector of desired appliance operation duration in $\mathbf{t}$.

TABLE I. Table of Notations

Symbol	*Description*
N	Number of appliances
T	Number of timeslots
a^n	nth appliance
$\boldsymbol{t}$	Timeslot vector
$\boldsymbol{s}^n$	Schedule vector of nth appliance
$\boldsymbol{d}$	Operation duration vector

III. Operation Types of Appliances

In this section we enumerate operation types of appliances.

A. Discrete Type

Discrete type is a common operation type of appliances. There are no restrictions in comparison to following operation types. Appliances in this type can operate and stop unrestricted number of timeslots.

B. One-Stop Type

Appliances in one-stop type can start and finish operation only once in time duration $\boldsymbol{t}$. Their schedule must be continuous in their operation periods. We should be careful when converting this type into constraints because the appliances in this type can start or finish operations outside of $\boldsymbol{t}$.

C. Multiple-Stop Type

Appliances in multiple-stop type can start and finish operation specific time F. We can divide this type in two cases:

- Max-Stop: appliances in this type can start and finish operation maximum F times.
- Fix-Stop: appliances in this type can start and finish operation exactly F times.

D. Stepped Type

Appliances in this type have stepped operation modes that differing energy consumption. The appliances can change modes during the operation and the state transition pattern may vary.

E. Cooldown Type

Appliances in this type cannot be restarted until after a certain period of time once they have been stopped.

F. Sequential Type

Appliances in this type must start operation after other specified appliance finishes its operation.

IV. Type-Constraint Conversion Methods

In this section, we propose conversion methods from operation types to optimization constraints. Note that appliances can have multiple types, so we can apply multiple conversion methods to a single appliance.

A. Discrete Type

The nth appliance have desired operation duration d^n during $\boldsymbol{t}$. We can simply represent this as a constraint:

$$\sum_{t \in \boldsymbol{t}} s_t^n = d^n.$$

Since discrete type is unrestricted, other types equally start from this constraint.

B. One-Stop Type

Since s_t^n is a 0-1 variable, $c_t^n = (s_{t-1}^n - s_t^n)^2$ must be 0 or 1. In particular, c_t^n is the change of the nth appliance's operation state. Appliances in one-stop type must change their state less then or equal to 2. If the nth appliance is one-stop type and scheduled to operate at t_1 or t_T, the number of state change will decrease 1 for each. This insight can be converted into a constraint:

$$\sum_{t=2}^{T} (s_{t-1}^n - s_t^n)^2 = 2 - s_1^n - s_T^n.$$

Note that the constraint is in quadratic form.

C. Multiple-Stop Type

If appliances in multiple-stop type have to operate F number of periods, the number of operation state changes is at most $2F$. Considering the conversion method of one-stop type, the number of state change should be decreased if the appliance is scheduled to operate at t_1 or t_T. Note that the constraint is in quadratic form, the constraint should be:

$$\sum_{t=2}^{T} (s_{t-1}^n - s_t^n)^2 = 2F - s_1^n - s_T^n.$$

In max-stop:

$$\sum_{t=2}^{T} (s_{t-1}^n - s_t^n)^2 \leq 2F - s_1^n - s_T^n.$$

This approach is simpler than separating appliance into logical components, as the method will be introduced for stepped type.

D. Stepped Type

If an appliance in this type has M stepped operation modes, the appliance can logically be separated into M component appliances. Each component appliance consumes "additional" energy increased from its lower state, except the first component representing the lowest energy consumption mode. Note that the number of appliances increased after the separation, so the input to the optimization model is changed. With this method we can represent stepped type appliances, without changing the optimization model or adding constraints that are difficult to understand.

It should be careful to add constraints corresponding to the appliance's step pattern. Here is an example of 2-stepped type application constraints:

$$\sum_{k \in \{a,b\}} \sum_{t=2}^{T} (s_{t-1}^k - s_t^k)^2 = 2 - s_1^k - s_T^k,$$

$$s_t^a \geq s_t^b.$$

In this example, a and b are logical components and a is the lower energy consumption mode and b is the higher energy consumption mode. Considering the second constraint, the higher energy consumption mode can only be activated when the lower energy consumption mode is activated. In this case the appliance is one-stop type and will operate in higher energy consumption mode once, during the one-stop period. Consequently, the actual energy consumption of the appliance is sum of two energy consumption mode when it is operating on higher energy consumption mode.

E. Cooldown Type

If an appliance cannot be restarted until after τ timeslots once they have been stopped, it can be represented like:

$$s_t^n - s_{t+1}^n + \frac{1}{\tau} \sum_{j=1}^{\tau} s_{t+1+j}^n \leq 1, \forall \mathrm{t} \leq T - \tau - 1.$$

If $s_t^n - s_{t+1}^n = 1$, the rest of the left-hand side must be zero. In other words, the appliance cannot be scheduled to operate τ timeslots after it finished its operation.

We can observe that if we have a cooldown type application, the number of constraints increase in proportion to τ.

F. Sequential Type

Representing sequential type application constraints is similar with representing stepped type application constraints. If appliance b must start operation after appliance a finishes its operation, the constraint should be like:

$$\frac{1}{T - t + 1} \sum_{j=t}^{T} s_j^a + s_t^b \leq 1.$$

V. Conclusion and Future Directions

In this paper, we proposed type-constraint conversion methods used for optimization problems in DR smart grid systems. With these methods we can represent appliances that varies energy consumptions while operating and we can represent dependencies between appliances. We found relationships of appliance operation types and the number of constraints to represent them. Also various optimization and scheduling schemes [9]-[12] can be adaptive for smart grid system and compare with proposed method as a future work.

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