Electrical Power and Energy Systems 97 (2018) 165–173

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Hierarchical control strategy for residential demand response considering time-varying aggregated capacity☆

Yi Tang[a,*], Qian Chen[a], Jia Ning[a], Qi Wang[a], Shuhai Feng[b], Yaping Li[b]

[a] School of Electrical Engineering, Southeast University, Sipailou 2#, Nanjing, Jiangsu Province 210096 PR China
[b] Power Automation Department, China Electric Power Research Institute, NARI Road 8#, Nanjing, Jiangsu Province 210003 PR China

ARTICLE INFO

Keywords:
Hierarchical control strategy
Residential demand response (DR)
Load aggregator (LA)
Aggregate capacity
User comfort level

ABSTRACT

Load control strategy has become a focus of researches, as demand-side resources are technically and economically desirable to relieve system power imbalance. In this paper, a hierarchical control strategy via load aggregator (LA) is proposed, considering both the evaluation of potential response capacity of large-scale residential loads and optimal allocation of response demand to each individual load. First, an aggregate model is established to exploit the time-varying potential response capacity of a population of residential loads. In the upper strategy, an equivalent response potential (ERP) index is created to quantitatively calculate the aggregate capacity and utilized to guide the allocation of total response demand to each LA. In the lower strategy, an optimal allocation model is built to determine the response status of each residential load per minute, ensuring end-user satisfaction and demand response requirements. The aggregate model and control strategy are verified valid through case studies. Furthermore, model accuracy and strategy implementation are discussed as well.

1. Introduction

With the high penetration of intermittent renewable generation and the remarkable increase in power transmission capacity, electric power system has been confronted with the hazard of severe short-term (minutes or even seconds) power shortage [1,2]. Such short-term power shortage will probably deteriorate into cascading failures or even large-scale blackouts if generation-side regulation is limited to provide the desired power capacity [3]. Thanks to the utilization of intelligent terminal devices, improvement of smart meter techniques and two-way communication technologies [4,5], demand response (DR) has become an alternative to alleviate power supply deficit by selectively curtailing loads [6].

There have been tremendous studies of demand-side load control strategy. Based on the literature review, load control strategies can be classified into two categories: one is control-architecture-based strategy and the other is control-timescale-based strategy [7–17]. Concerning the former one, Hiskens et al. [7] have summarized that there are three kinds of load control architectures, including centralized load control architecture, distributed load control architecture, and hierarchical load control architecture. When it comes to control-timescale-based strategy, it can be categorized into three types: primary load regulation (second-level), secondary load regulation (minute-level), and tertiary load regulation (24-h-level), which is similar to generation-side frequency control strategy [9,12–14]. The objective of our paper is to remedy the minute-level imbalance between generation and consumption side using the potentials of large-scale residential loads. In order to manage such a large population of small loads, a hierarchical load control architecture via aggregators is adopted in this paper.

Notwithstanding the significant effort in load control strategies to manage frequency and energy imbalances in power systems, the existing literature has barely quantitatively evaluated the time-varying potential capacity of demand-side residential loads. Most of them assumed the potential response capacity of demand-side resources was a fixed value (e.g. several MW) or a fixed percentage of the total controllable loads when implementing their control strategies. For example, Trudnowski et al. [18] stated that about 20% of residential load could be interrupted for short periods; Kamwa et al. [19] assumed that the total size of the controllable loads was 62.4 MW (1% of total load). With the improvement of smart meter techniques and two-way communication technologies, potential response capacity of residential loads can be evaluated quantitatively nowadays.

The potential response capacity of residential loads, especially thermostatically controlled loads (TCL), changes according to their physical operating feature. For instance, only when an air conditioner (AC) stays in the ON status can it possess the ability of providing

☆ This work is supported by the National Natural Science Foundation of China (Grant No. 51577030) and State Grid Corporation of China Project (SGJS0000DKJS1700263).
* Corresponding author.
E-mail addresses: tangyi@seu.edu.cn (Y. Tang), fengshuhai@epri.sgcc.com.cn (S. Feng).

https://doi.org/10.1016/j.ijepes.2017.11.001
Received 30 March 2017; Received in revised form 1 September 2017; Accepted 4 November 2017
0142-0615/ © 2017 Elsevier Ltd. All rights reserved.

response power to system. In other words, residential loads may be unavailable for response during the power shortage period. Because of such kind of physical operating characteristics, the aggregate potential capacity of large-scale residential controllable loads is time varying rather than a fixed value. Therefore, an aggregate model is needed for evaluation of potential capacity of residential loads.

Aggregate models for active residential loads have been investigated over the past several years [20–26]. However, few papers have taken physical operating characteristics of TCLs and EVs, together with user comforts and DR policy (e.g. response times) into consideration at the same time. Kalsi et al. [20] presented an aggregate model for TCLs, considering a second-order effect to estimate the transient dynamics of DR. Meanwhile, Callaway et al. [22] studied the temperature state evolution of TCLs through Markov chain models, and built a model-estimator-controller to balance the system power. Nevertheless, the impact of user comforts is neglected. The shortcoming was then investigated by Bouffard et al. [24], who employed a physical-based model to calculate on-time statistics of 1000 electric water heaters (EWH) while accounting for user satisfaction. Besides, the popularity and response potentials of electric vehicles (EV) should also be considered because EV loads can provide response power to system without affecting end-user performance for significant periods [25–27]. Therefore, all the associated factors such as physical characteristics, end-user behaviors and DR policies shall be considered in aggregate models.

In this paper, an aggregate model considering load physical dynamics, end-user comforts and constraints of response times is established. An equivalent response potential (ERP) index is then created to calculate the potential response capacity quantitatively. In the upper layer of our control strategy, control center allocates the total response demand to each LA according to the ERP index; in the lower layer, each LA further determine response status of each individual load per minute, considering control cost, user comfort level, response constraints and the scheduling precision. The strategy is verified through a case study.

The contributions of our paper can be summarized as the following three aspects.

- An aggregate model for residential controllable loads is established to evaluate the time-varying response capacity, with physical operating characteristics, end-user comforts and constraints of response times considered.
- An Equivalent Response Potential (ERP) index is created to calculate the aggregate response capacity of each LA, and then allocate total imbalance power to them according to the ERP index.
- Response status of each residential load per minute is explored using a multi-constrained optimization model, with control cost, user comforts, response constraints and scheduling precision considered.

The remaining of this paper is organized as follows. In Section 2, an aggregate model for residential loads is established. In Section 3, total potential response capacity of residential loads is evaluated quantitatively. A hierarchical load control strategy based on the aggregated response capacity is proposed in Section 4 and validated through a case study in Section 5. Discussions and conclusions are given in Section 6 and 7.

2. An aggregate model for residential DR resources

In this section, an aggregate model based on individual load characteristics is set up for large-scale residential loads, considering single load dynamics, user comfort indices, and demand response constraints.

2.1. Physical-based load models

Physical-based single load model in [28] is employed to describe the heat transfer process of AC loads and WH loads, together with the charging process of EVs.

2.1.1. Thermal dynamic model of an AC load

The heat transfer process of an AC load is associated with many factors, including house structures, the electrical characteristics of space cooling or heating unit, etc. Thermal dynamic model of an AC load can be simplified into an input-output model where the input signal is working mode and the model output is indoor temperature. For each time step t, the indoor temperature can be calculated as

$$T_{AC,t+1} = T_{AC,t} + \Delta t\cdot\frac{G_t}{\Delta c} + \Delta t\cdot\frac{C_{AC}}{\Delta c}\cdot S_{AC,t} \tag{1}$$

where $T_{AC,t+1}$ and $T_{AC,t}$ are the indoor temperature at time $t+1$ and t, respectively; $\triangle t$ is the time interval; G_t is the heat gain rate of the house during timeslot t; Δc is the calories required each time the indoor temperature is raised by 1°C; C_{AC} is cooling/heating thermal capacity; $S_{AC,t}$ is the status of AC during timeslot t ($S_{AC,t} = 0$ at the OFF status, and $S_{AC,t} = 1$ at the ON status).

2.1.2. Thermal dynamic model of a WH load

Similar to the thermal dynamic model of an AC load, the heat transfer process of a WH load is also influenced by different factors, including tank volume of WH, the electrical characteristics of water-cooling or heating unit, etc. Therefore, WH model can also be simplified into an input-output model where the input signal is working mode and the model output is water temperature. For each time step t, water temperature can be calculated as

$$T_{WH,t+1} = \frac{T_{WH,t}(V_{WH} - fl_t\cdot\Delta t)}{V_{WH}} + \frac{T_{in}fl_t\cdot\Delta t}{V_{WH}} + \alpha\cdot P_{WH} + \xi \tag{2}$$

where $T_{WH,t+1}$ and $T_{WH,t}$ are the water temperature at time $t+1$ and t, respectively; V_{WH} is the volume of tank; fl_t is the water flow rate during timeslot t; T_{in} is the temperature of inlet water; α is the increase of water temperature per unit time at rated power; P_{WH} is the rated power of WH; ζ is the decrease of water temperature per unit time in the natural cooling state.

2.1.3. Charging model of an EV load

Different from the heat transfer process of thermal loads, modeling EV load should consider the charging process. To model the charging process, several essential parameters cannot be ignored, such as rated charging power, battery rated capacity and state-of-charge (SOC), etc. Therefore, the battery SOC is determined by

$$S_{EV,t+1} = S_{EV,t} + P_{EV}\frac{\Delta t}{C_{batt}} \tag{3}$$

where $S_{EV,t+1}$ and $S_{EV,t}$ are the amount of energy left in the battery at time $t+1$ and t, respectively; P_{EV} is the rated power of EV; C_{batt} is the battery rated capacity.

2.2. Quantitative representation of user comfort level

User comfort of thermal loads can be affected by temperature, humidity, and flow rate, etc. Among all the factors, temperature has the most critical influences on user comfort, so user comfort level of AC loads and WH loads are calculated by (4) and (5).

$$I_{AC} = \frac{T_{AC} - T_{c,AC}}{\Delta T_{AC}} \tag{4}$$

$$I_{WH} = \frac{T_{c,WH} - T_{WH}}{\Delta T_{WH}} \tag{5}$$

where I_{AC}, I_{WH} are user comfort indices of AC and WH; T_{AC}, T_{WH} are the actual temperature of AC and WH; $T_{c,AC}$, $T_{c,WH}$ are the optimum temperature of AC and WH; ΔT_{AC}, ΔT_{WH} are the interval length of temperature comfort zone.

Download English Version:

https://daneshyari.com/en/article/6859466

Download Persian Version:

https://daneshyari.com/article/6859466

Daneshyari.com