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Operating reserve capacity evaluation of aggregated heterogeneous TCLs with price signals

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HIGHLIGHTS

- A thermostatically controlled load (TCL) model considering consumer behaviors is developed.
- Consumer satisfaction is considered in the decision making process by fuzzy set method.
- Operating reserve capacity (ORC) of TCLs is evaluated based on price signals.
- A kernel density estimation method is proposed to evaluate ORC with insufficient data.

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ABSTRACT

Thermostatically controlled loads (TCLs) have been studied to provide operating reserve for maintaining power balance between supply and demand. However, operating reserve capacity (ORC) supplied by aggregated TCLs is difficult to evaluate, due to the insufficient information of heterogeneous TCLs and consumer behaviors. This paper proposes a quantitative ORC evaluation method for large-scale aggregated heterogeneous TCLs without sufficient measurement data. Firstly, an individual TCL model on account of consumer behaviors is developed to characterize the impact of fluctuated electricity prices and different thermal comfort requirements. Secondly, a novel optimization model of heterogeneous TCLs, which can guarantee consumer satisfaction, is proposed to provide operating reserve for power systems. Thirdly, the probability density estimation (PDE) method is developed to evaluate the ORC provided by large-scale heterogeneous TCLs with insufficient data. Numerical studies illustrate the effectiveness of the proposed models and methods.

1. Introduction

The increasing penetration of renewables brings more fluctuations to electric power systems [1]. Therefore, the requirement of operating reserve capacity (ORC) for maintaining power balance between supply and demand is larger [2]. Conventionally, operating reserve is provided by generating units, such as thermal power units [3]. However, the share of traditional generators in power generation is decreasing and may not be able to satisfy the requirement of ORC [4]. Moreover, information and communication technology have developed, which makes it possible for demand side resources (DSRs) to provide operating reserve by reducing or shifting loads [5,6].

Thermostatically controlled loads (TCLs), such as heating, ventilation and air conditioning, account for a large share of power consumptions. For example, the power proportion of residential air conditionings reaches up to 40% during summer peak load periods in China [7,8]. Moreover, consumer's comfort will not be affected when the operating states of TCLs are adjusted temporarily [9,10]. Therefore, TCLs have a great potential to be controlled and provide ORC [11]. A TCL model is developed in [12] to participate in operating reserve services. Ref. [13] proposes centralized control methods on TCLs to provide operating reserve. The comparison of distributed system and centralized system is studies in [14]. Besides, a load following method is developed in [6] to enhance the safety and stability of the power system. An operational planning framework for aggregated TCLs is developed to improve the efficiency in day-ahead scheduling and real-time operation [15,16].

Price-based demand response (DR) is one of the main approaches for DSRs providing operating reserve services [10,17]. Consumers can adjust the power consumption to respond the variable electricity prices [18] and reduce their electricity expenditure [19,20]. Moreover, the social welfare is improved based on the price-based DR [21] and the optimization mechanism [22,23]. However, two practical problems of ORC evaluation are relatively less studied: On the one hand, the lack of

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Nomenclature

Acronyms

ORC	operating reserve capacity
TCL	thermostatically controlled load
PDE	probability density estimation
ME	moment estimation
EER	energy efficiency ratio
DR	demand response
DSR	demand side resource
TSK	Takagi-Sugeno-Kang
CM	comfortable temperature
CL	cool temperature
HT	hot temperature
LW	low electricity cost
AP	acceptable electricity cost
HG	high electricity cost

Variables and parameters

T_{set}	set temperature of a TCL
T_{room}	room temperature
S	operation state of a TCL
ΔT	hysteresis band of room temperature
P	power consumption of a TCL
P_r	rated power of a TCL
p	electricity price
C	electricity cost
Q	refrigerating capacity of a TCL
H_r	equivalent thermal conductance of a room
T_{ext}	ambient temperature
C_{room}	thermal mass of a room
y_s	consumer satisfaction value
μ	membership values
P^k	average power of the k−th TCL
ΔP^k	power deviation of the k−th TCL
P_{ORC}	ORC provided by aggregated heterogeneous TCLs
$\widehat{f}_h$	joint probability density function
N_s	number of TCLs with known parameter
N	total number of TCLs
$\widehat{P}_{avg}$	evaluation value of the average power P_{avg}
$\widehat{P}_{ORC}$	evaluation value of the total ORC P_{PRC}
K	kernel function
h	bandwidth of the K
α	satisfaction weight between the electricity cost and the room temperature
e_m	error of the estimated ORC

consumer behavior model makes it difficult to evaluate the ORC provided by aggregated TCLs. Consumers have diverse preferences on power consumption when the electricity prices are fluctuated [24–26]. Therefore, the consumer decision making process is relatively vague. On the other hand, it is impractical to obtain all the heterogeneous parameters, especially for large-scale TCL aggregations. Therefore, ORC has to be evaluated based on insufficient data of aggregated heterogeneous TCLs.

In this paper, an ORC evaluation method for large-scale aggregated heterogeneous TCLs is proposed based on insufficient measurement data. Firstly, an individual TCL model is developed to evaluate ORC provided by a consumer. Then, satisfaction index is quantified by the fuzzy set method. Consumer's decision-making process and behaviors are simulated with the aim of maximizing satisfactions. Finally, the probability density estimation (PDE) method is proposed to evaluate ORC with insufficient data. The main contributions of this paper can be summarized as follows:

(1) The individual TCL model integrating electric-thermal characteristics and consumer behaviors, is developed for providing ORC considering consumer satisfaction with price signals, which has been rarely studied in the existing literatures.
(2) Consumer preferences on the electricity price and the room temperature are modeled with the fuzzy set method. In this manner, consumer's cognition and trade-off in decision making process can be quantified for consumer behavior simulation.
(3) The PDE method is proposed to evaluate the ORC of large-scale heterogeneous TCLs without sufficient measurement data. Compared with the traditional moment estimation method, the evaluation precision of ORC is improved significantly.

This paper is organized as follows. Section 2 develops an individual TCL model on account of consumer behaviors. Section 3 introduces the ME and the PDE method for estimation with insufficient data, respectively. The effectiveness of the proposed model and methods are illustrated by numerical studies in Section 4. Finally, Section 5 concludes this paper.

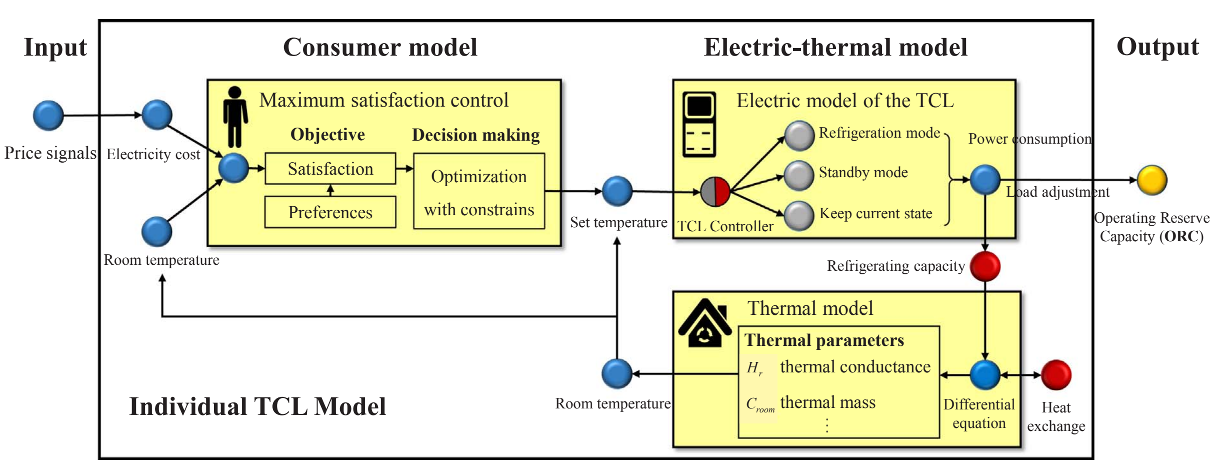

Fig. 1. The framework of the individual TCL model.

2. Individual TCL model

2.1. Framework and electric-thermal model

To evaluate ORC provided by aggregated TCLs, the framework of an individual TCL model is proposed, as shown in Fig. 1. The individual TCL model comprises the consumer model and the electric-thermal model, the latter of which is divided into electric model of the TCL and the thermal model of a room. Moreover, the input and output of the individual TCL model are price signals and ORC, respectively [3,28].

The consumer model is developed to simulate the consumer behaviors, which considers the electricity cost and room temperature. Based on the preference of the two factors, index of consumer's satisfaction is defined. Then, optimal control strategy is designed to maximize consumers' satisfaction level. The modeling details will be discussed in the next two subsections.

It is assumed that TCLs work in refrigeration mode during summer period. The operating state of the TCL is decided by the set temperature $T_{set}(t)$ and the current room temperature $T_{room}(t)$, which can be expressed as

$$S(t) = \begin{cases} 1, T_{room}(t) \geqslant T_{set}(t) + \Delta T \\ 0, T_{room}(t) \leqslant T_{set}(t) - \Delta T \\ S(t-\tau), else \end{cases} \tag{1}$$

where $S(t)$ is the operating state of the TCL; ΔT represents the hysteresis band for room temperature control; τ is the time interval of each control. The TCL will turn to refrigeration mode ($S(t) = 1$) if the room temperature is higher than the set temperature, while the TCL will turn to standby mode ($S(t) = 0$) if the room temperature is lower than the set temperature.

The power consumption and the electricity cost of the TCL can be expressed as

$$P(t) = P_r \cdot S(t) \tag{2}$$

$$C(t) = P(t) \cdot p(t) \tag{3}$$

where $P(t)$ and P_r is the power consumption and the rated power of the TCL, respectively; $C(t)$ is the electricity cost; $p(t)$ is the electricity price.

Moreover, the refrigerating capacity provided by the TCL can be expressed as

$$Q(t) = EER \cdot P(t) \cdot \tau \tag{4}$$

where EER is the energy efficiency ratio between the power consumption and the refrigerating capacity.

The thermal model of the room can be described as [29]

$$T_{room}(t) = T_{room}(t-\tau) + \frac{Q - H_r(T_{room}(t-\tau) - T_{ext})}{C_{room}} \tag{5}$$

where H_r is the equivalent thermal conductance between the indoor air and the ambient air; T_{ext} and C_{room} are the ambient temperature and thermal mass of the room, respectively.

2.2. Consumer satisfaction quantization

It is crucial to ensure consumer satisfaction when controlling electricity consumption of TCLs so that consumers are willing to participant in DR programs. TCL consumer satisfaction is mainly affected by their preferences for the room temperature and the electricity cost, which tend to be unspecific and may change over time with high uncertainty. The fuzzy set method is able to model the qualitative aspects of human knowledge without precise quantitative analysis [30,31]. Therefore, a typical fuzzy model (i.e., TSK (Takagi-Sugeno-Kang) fuzzy model [32]), which is adapted at processing intermediate values just like human cognition, is proposed to quantify consumer satisfaction, as shown in Fig. 2.

Consumer's cognitions can be modeled by the approach of fuzzy set method. Three fuzzy subsets of room temperatures T_{room} are defined to represent different feelings, including cool (CL), comfortable (CM) and hot (HT). Similarly, three fuzzy subsets of electricity costs C including low (LW), acceptable (AP) and high (HG) are defined to express the consumer sensitivity. The membership values of each fuzzy subset could be derived from adopted membership functions.

Each combination of the above subsets will have corresponding consumer satisfaction values. Consumer satisfaction value depends on the transition from the temperature and cost subsets. In TSK fuzzy model, the transition is defined as a form of IF-THEN rules with a linear function integrating the room temperature and the electricity cost. A typical fuzzy rule to calculate satisfaction can be expressed as

$$\text{If}(C \text{ is LW}) \quad \text{and } (T_{room} \text{ is CM}) \text{ Then } (y_s^i = f^i(C, T_{room})) \tag{6}$$

where y_s^i is the consumer satisfaction value of the i^{th} fuzzy rule. $f^i(\cdot)$ is the linear function of the i^{th} fuzzy rule, which can be expressed as

$$f^i(C, T_{room}) = a_0^i + a_1^i \cdot C + a_2^i \cdot T_{room} \tag{7}$$

where a_0^i, a_1^i, a_2^i are parameters for the i^{th} consumer. Consumers' trade-off between room temperature T_{room} and electricity cost C can be simulated based on reasonable choices of these parameters, whose example is shown in Section 4.1.

From Eqs. (6) and (7), the satisfaction index can be calculated by the function $f^i(\cdot)$, if the electricity cost C is LW and the room temperature T_{room} is CM, respectively. Similarly, all combinations of the subsets can be calculated according to different parameters of heterogeneous customers. In this manner, consumer satisfaction y_s can be expressed as the output of TSK fuzzy model [32]

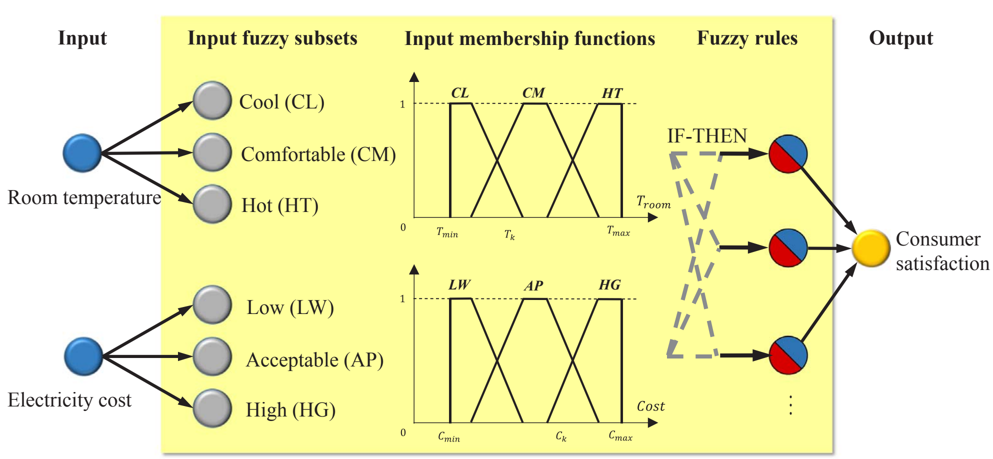

Fig. 2. The framework of fuzzy set method.

$$y_s = \sum_{i=1}^{R} (\mu_C^i(C)\cdot\mu_T^i(T_{room})\cdot y_s^i) \Big/ \sum_{i=1}^{R} (\mu_C^i(C)\cdot\mu_T^i(T_{room})) \tag{8}$$

where μ_C^i,μ_T^i are the membership functions of the different fuzzy subsets corresponding to the i^{th} fuzzy rule, whose subscript 'C' and 'T' indicate the fuzzy subsets of the electricity cost C and the room temperature T_{room}, respectively. R is the number of the fuzzy rules. From Eqs. (6)–(8), the TSK fuzzy model is able to output the quantified consumer satisfaction based on the inputs of the room temperature and the electricity cost.

2.3. Maximum satisfaction control strategies

According to the economic man hypothesis [33], it is assumed that each individual is rational with complete knowledge and aims to maximize personal utility. Therefore, the decision making process of TCL consumer is to maximize the satisfaction, which is determined by the electricity cost and the room temperature. In this way, the control strategy of the set temperature is to maximize satisfaction y_s and is expressed by

$$Max \sum_{i=1}^{R} (\mu_C^i(C)\cdot\mu_T^i(T_{room})\cdot y_s^i) \Big/ \sum_{i=1}^{R} (\mu_C^i(C)\cdot\mu_T^i(T_{room})) \tag{9}$$

where y_s is the consumer satisfaction expression shown in Eq. (8).

The constraints are as following:

(1) TCL model in Eqs. (1) and (2).
(2) Cost function in Eq. (3).
(3) Thermal model in Eqs. (4) and (5).
(4) Inequality constraint:

$$T_{\min} \leqslant T_{set}(t) \leqslant T_{\max} \tag{10}$$

The objective function of the Eq. (10) is complex and nonlinear, which lead to a nonlinear mixed-integer programming. In practice, the set temperature of a TCL is an integer and limited in a certain range. For example, the set temperature range of TCL is between 18 °C and 30 °C in general, where only the integer temperatures could be set. There are few temperature alternatives for consumer decisions. Therefore, traversal method is applied to solve this optimization. The calculation steps are as following:

Step 1. List alternative set temperatures of the TCL.
Step 2. Calculate the average power and electricity cost in different set temperatures.
Step 3. Calculate the consumer satisfaction values by the fuzzy model.
Step 4. Compare each satisfaction values and choose the set temperature T_{set} corresponding to maximum satisfaction as the optimal decision.

As shown in Fig. 1, the set temperature T_{set} serves as an intermediate variable in the process from input (price signals) to output (power consumption). After obtaining optimal T_{set}, power consumption P can be calculated based on the electric-thermal model and then, ORC can be evaluated.

3. ORC evaluation of aggregated heterogeneous TCLs

The individual TCL model involves many parameters and variables, which could influence the output more or less. Aggregators or operators of power systems are required to obtain all the values to evaluate the total ORC. In general, ORC evaluation can be calculated in

$$P_{ORC}(p_0,p_1) = \sum_{k=1}^{N} \Delta P^k(p_0,p_1) \tag{11}$$

where N is the total number of TCLs, and $\Delta P^k(p_0,p_1)$ is a function of the current price p_0 and target price p_1, which can be expressed as

$$\Delta P^k(p_0,p_1) = P^k(p_0) - P^k(p_1) \tag{12}$$

where $P^k(p)$ is the average power of the k-th TCL.

In practice, estimation sometimes has to be made without sufficient information due to limited measurements or equipment failures. For example, the thermal parameters (e.g. equivalent thermal conductance and thermal mass) cannot be collected easily because the values vary with time, locations and buildings. These parameters or variables may be obtained via survey by field works, or by parameter fitting from actual monitoring data. But it costs too much to obtain these parameters of every individual, especially for a large-scale heterogeneous aggregation. Thus, ORC provided by TCLs has to be evaluated based on insufficient data. In this section, two feasible estimation methods are given: moment estimation (ME) method and probability density estimation (PDE) method.

3.1. Moment estimation method

Moment estimation (ME) method, as one of the point estimation methods [27], is applied in ORC evaluation. The evaluation steps are shown in Fig. 3.

It is assumed that the number of known TCLs is N_s of the whole number N. The mean value of ORC based on N_s TCL data is calculated. Then, the total ORC of all the N TCLs is estimated, which can be expressed as

$$\widehat{P}_{ORC}(p_0,p_1) = \frac{N}{N_s} \sum_{k_s=1}^{N_s} \Delta P^k(p_0,p_1) \tag{13}$$

3.2. Probability density estimation method

The probability density estimation (PDE) method is divided into two stages. Kernel density estimation is used in the first stage to estimate probability density function based on the limited measurement data. In the second stage, the ORC of aggregated TCLs is evaluated by calculating the expectation of power consumption.

3.2.1. The first stage

Kernel density estimation is one of non-parametric PDE methods to estimate the probability density distribution. Compared with parametric methods, the main advantage is the extensive applicability in unknown densities, especially for irregular shapes [34]. Moreover, the smoothness of kernel density results helps to avoid statistical errors compared with other non-parametric density estimation methods, such as frequency histogram. In Fig. 4, a multi-peak density function is taken as an example to illustrate the principle of kernel density estimation.

There are 6 known data points marked in black solid lines. Every known data point corresponds to a kernel function, which is normal distribution indicated by red[1] dashed curves. These kernel functions are summed for the kernel density estimation, which is shown as the blue solid line.

In this way, the density of a parameter could be estimated based on the data with the least prior knowledge. To address this process, let $(H_r^1,H_r^2,...,H_r^{N_s})$ be independent and identically distributed variables of equivalent thermal conductance H_r, where N_s is the known data number in the whole number N. The estimated probability density $\widehat{f}_{hH_r}$ can be expressed as

$$\widehat{f}_{hHr}(H_r) = \frac{1}{N_s h_{Hr}} \sum_{i=1}^{N_s} K\left(\frac{H_r - H_r^i}{h_{Hr}}\right) \tag{14}$$

[1] For interpretation of color in Figs. 4, 7, 8 and 10, the reader is referred to the web version of this article.

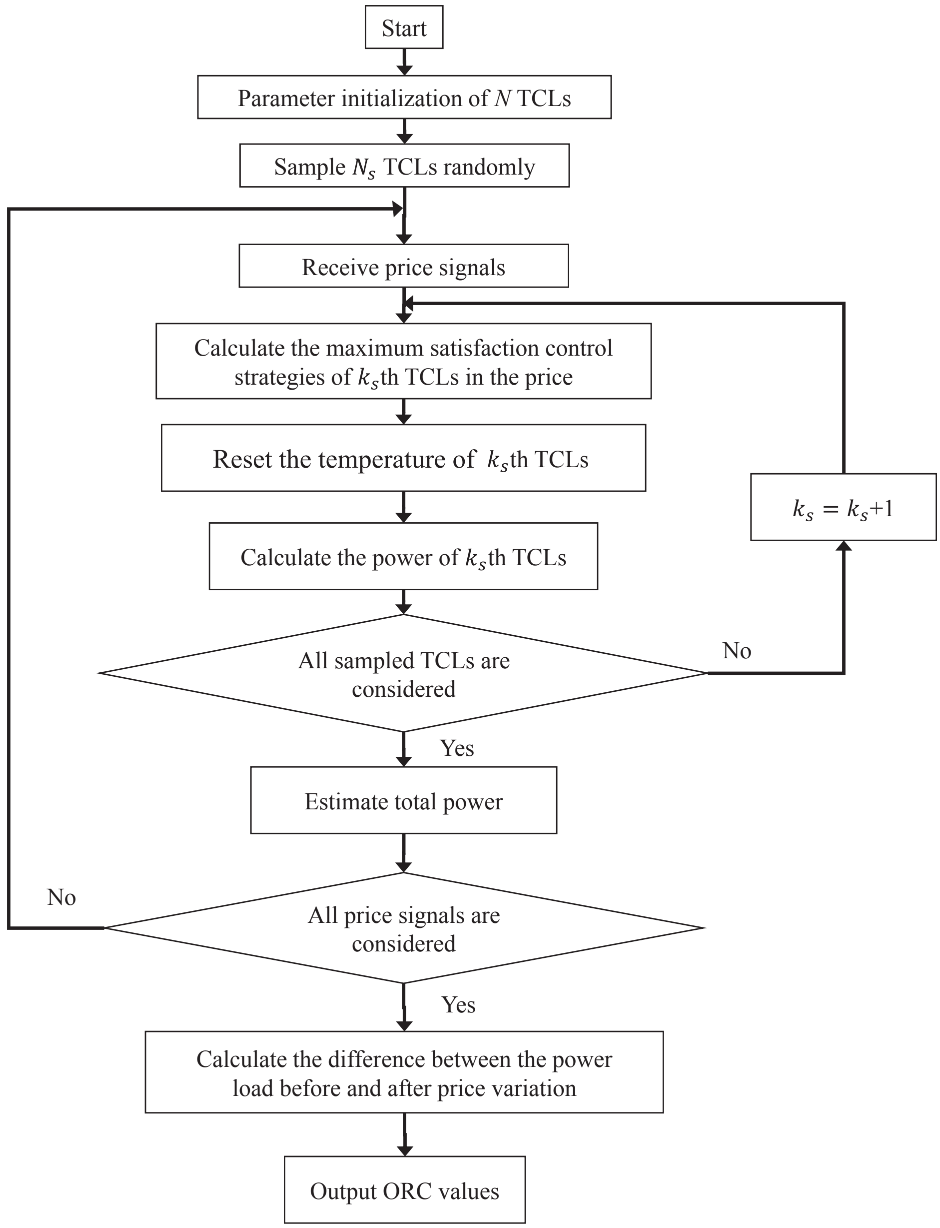

Fig. 3. The flow chart of ME method.

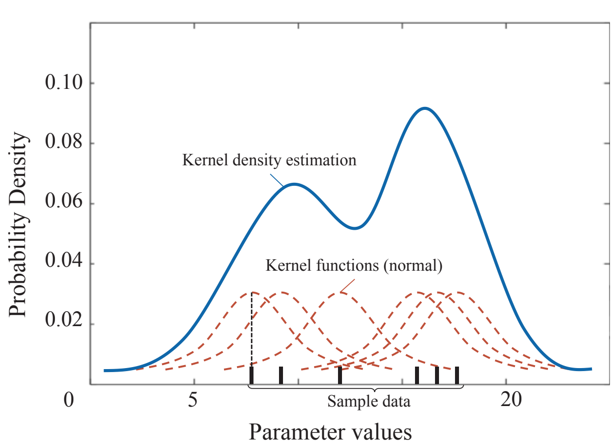

Fig. 4. The principle of kernel density estimation.

where $K(\cdot)$ is the kernel function, which is nonnegative and integral value is 1. There are several kernel functions can be used, such as uniform, normal (Gaussian), Epanechnikov and others [34]. Considering the convenient mathematical properties, normal kernel function is applied:

$$K(x) = \frac{1}{(2\pi)^{n/2}}\exp\left(-\frac{x^2}{2}\right) \tag{15}$$

The h_{Hr} is the bandwidth of the kernel $K(\cdot)$, which is required to be chosen strictly for the trade-off between the deviation of the estimator and its variance. If the bandwidth is large, the results will be too smooth and omit some important information. On the contrary, the results will contain lots of noises if the bandwidth is small. Different bandwidth choices will lead to completely different estimation results. To minimize the mean integrated squared error [35], the rule-of-thumb bandwidth estimator method is adopted for normal kernel [36]

$$h_{Hr} = (4/3N_s)^{1/5}\hat{\sigma}_{Hr} \tag{16}$$

where $\hat{\sigma}_{Hr}$ is the standard deviation of H_r.

Similarly, the probability density function $\widehat{f}_{hC_{room}}$ of the thermal mass of the room C_{room} can be obtained based on the kernel density estimation.

In order to evaluate the mean thermal potential, the joint density function of H_r and C_{room} should be derived from the marginal density functions of $\widehat{f}_{hC_{room}}$ and $\widehat{f}_{hH_r}$. H_r is mainly influenced by the room area and materials of walls, whereas C_{room} primarily depends on the room space and the air heat capacity. Hence, there is no direct relationship between H_r and C_{room}, which indicates the independence of the two parameters. The joint density function $\widehat{f}_h$ can be expressed as

$$\widehat{f}_h(C_{room},H_r) = \widehat{f}_{hC_{room}}(C_{room})\cdot\widehat{f}_{hH_r}(H_r) \tag{17}$$

From Eqs. (14)–(17), the joint density function can also be extended to multi-dimension if the parameters are independent with each other.

3.2.2. The second stage

Mean value of individual power consumption can be obtained by calculating the probability expectation, which is described as

$$\widehat{P}_{avg}(p_0) = \int_{C_{room}}\int_{H_r}\widehat{f}_h(C_{room},H_r)\cdot P_{avg}(p_0,C_{room},H_r) \tag{18}$$

where $\widehat{P}_{avg}$ is the expectation of TCL power at the price p_0; x,y represent estimated parameters.

The ORC of the TCL can be evaluated as

$$\widehat{P}_{ORC}(p_0,p_1) = N\cdot(\widehat{P}_{avg}(p_0)-\widehat{P}_{avg}(p_1)) \tag{19}$$

The total ORC provided by the aggregated heterogeneous TCLs can be calculated as the flow chart in Fig. 5.

Table 1
Fuzzy subsets of the room temperature T_{room}.

Fuzzy subsets	Min	Up-Min	Up-Max	Max
CL	–	–	21.0	24.0
CM	21.0	24.0	26.0	29.0
HT	26.0	29.0	–	–

Table 2
Fuzzy subsets of the electricity cost C.

Fuzzy subsets	Min	Up-Min	Up-Max	Max
LW	–	–	1.0	2.0
AP	1.0	2.0	4.0	5.0
HG	4.0	5.0	–	–

4. Case studies

This section proves the efficiency of the proposed model and

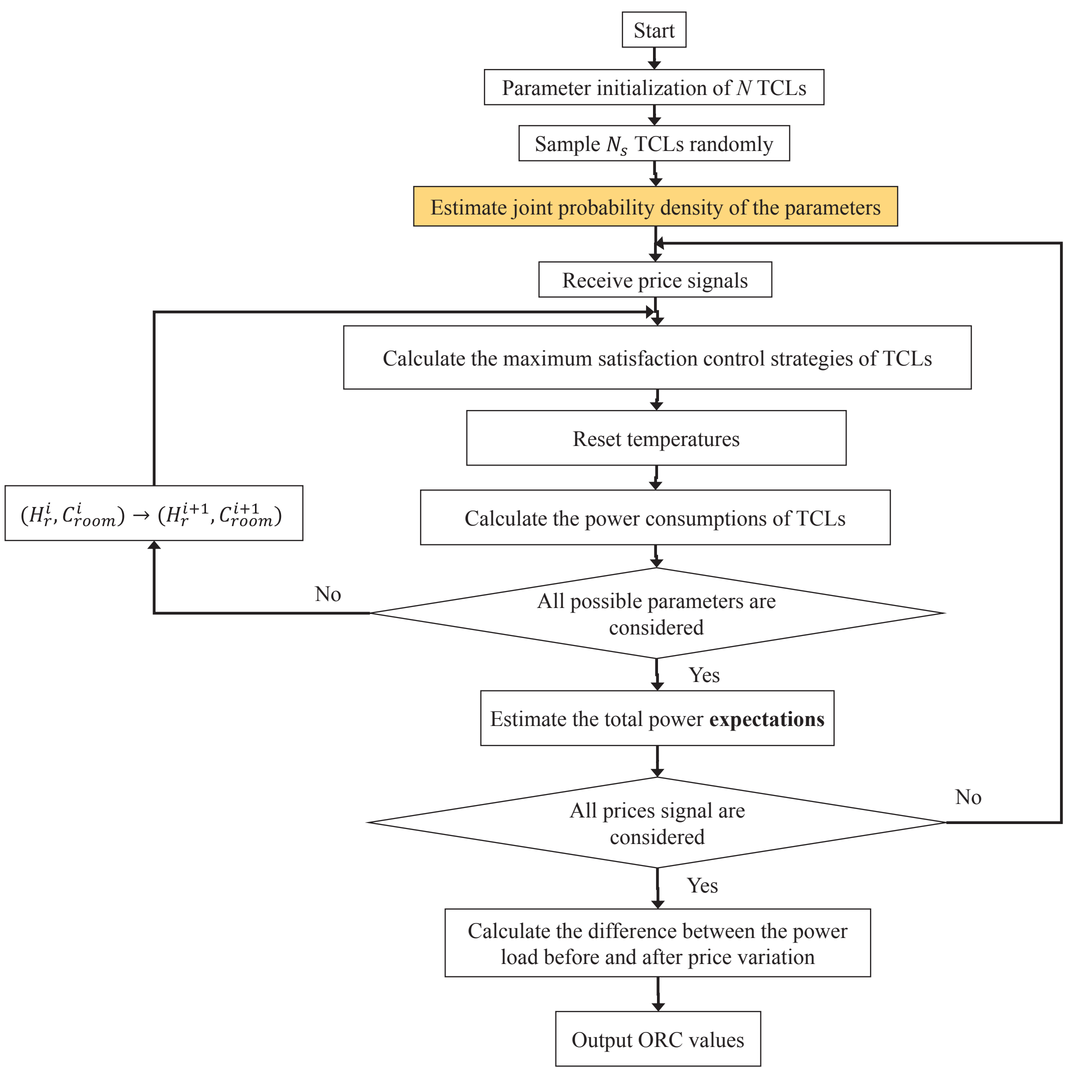

Fig. 5. The flow chart of PDE method.

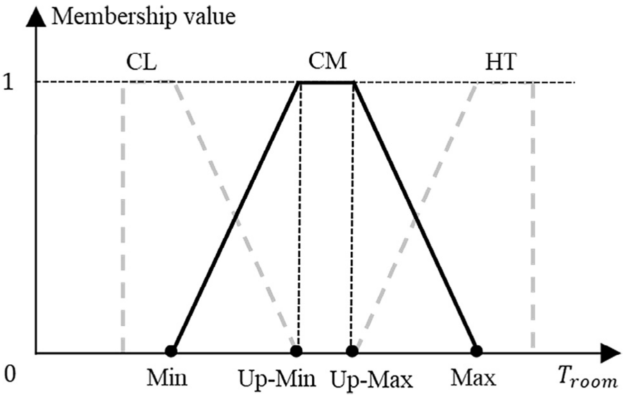

Fig. 6. Fuzzy subset example of CM (the comfortable feeling of the room temperature).

Table 3
Fuzzy rules of individual TCL model.

$f^i(\cdot)$	CL	CM	HT
LW	$1-\alpha$	1	$1-\alpha$
AP	$\alpha\cdot(1-\alpha)$	α	$\alpha\cdot(1-\alpha)$
HG	$\alpha^2\cdot(1-\alpha)$	α^2	$\alpha^2\cdot(1-\alpha)$

methods by case studies. Section 4.1 introduces the test system. Section 4.2 analyzes the accuracy of the ME method and the PDE method. Section 4.3 represents a real application of ORC evaluation in an actual case study.

4.1. The test system

In the test system, the ambient temperature is 30 °C. The total number of TCLs N is 20,000, where only 100 TCLs can be randomly measured. The rated power P_r of TCL is assumed to be 2 kW. The energy efficiency radio (EER) is 3.0. ΔT is set to be 1 °C. It is assumed that the thermal mass of the room C_{room} (kJ/°C) obeys normal distribution, which is $C_{room} \sim N(12,3.6^2)$. In order to generalize the distribution of equivalent thermal conductance H_r (kW/°C), half of H_r follows $N(1.5,0.4^2)$ and the other half follows $N(0.8,0.2^2)$ [3].

The initialized fuzzy subsets of the room temperature and the electricity cost are shown in Table 1 and Table 2, respectively [32]. Fig. 6 shows the example of fuzzy subset.

In addition, the fuzzy rules are shown in Table 3. The parameter α is the weight of satisfaction to the different factors, indicating the consumer's trade-off between room temperature and electricity cost. The weight of room temperature is heavier with a larger α. All the α are assumed to follow uniform distribution $\alpha \sim U(0,1)$.

Three cases are considered to illustrate the efficiency of proposed methods:

Case 1: Direct summation based on sufficient parameters of 20, 000 TCLs. This case can be regard as actual value.
Case 2: Moment estimation (ME) method based on insufficient parameters of 100 TCLs.
Case 3: Probability density estimation (PDE) method based on insufficient parameters of 100 TCLs.

To compare this the estimation performance of the two method, the error of the estimated ORC is defined as

$$e_m = |\widehat{P}^{m}_{ORC} - \widehat{P}^{1}_{ORC}|/\widehat{P}^{1}_{ORC} \quad (m = 2,3) \tag{20}$$

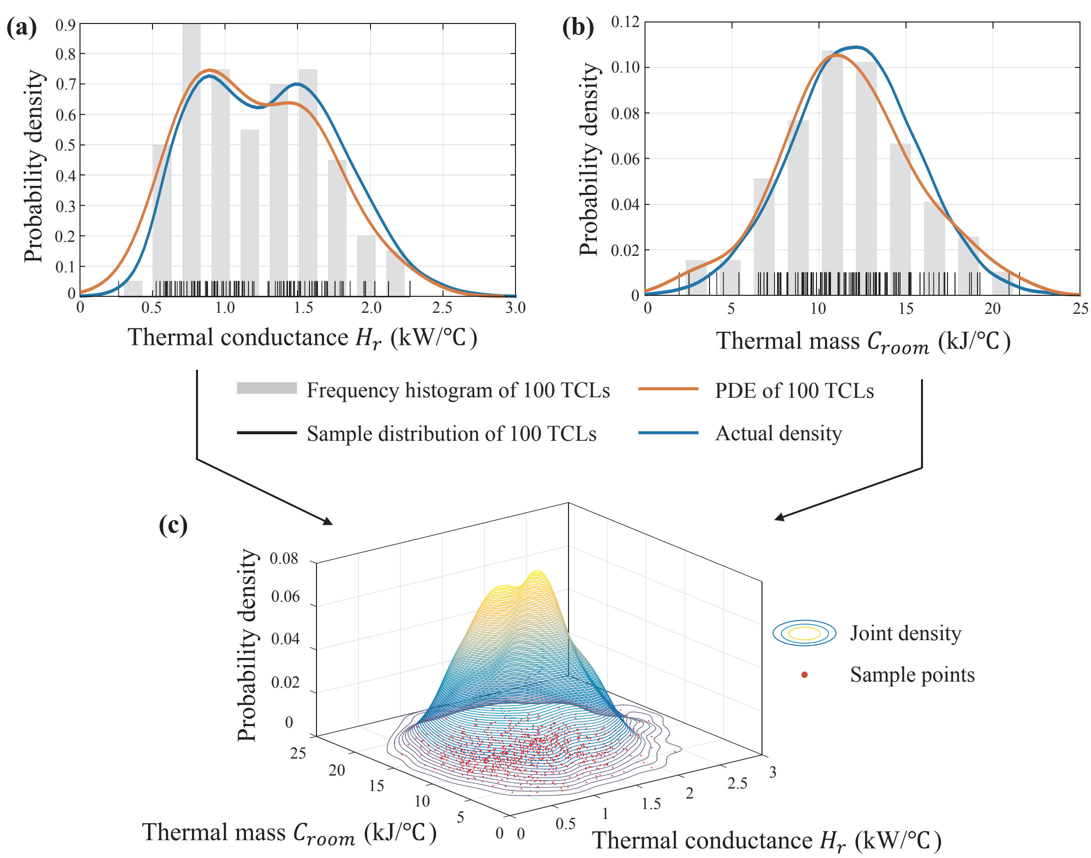

Fig. 7. Density estimation performances of PDE method.

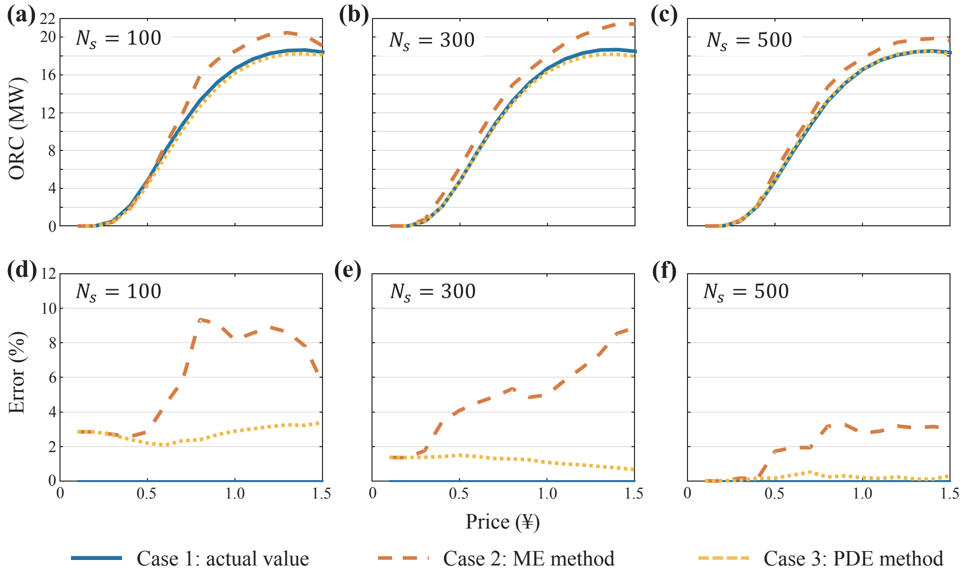

Fig. 8. ORC evaluation performances of the two methods.

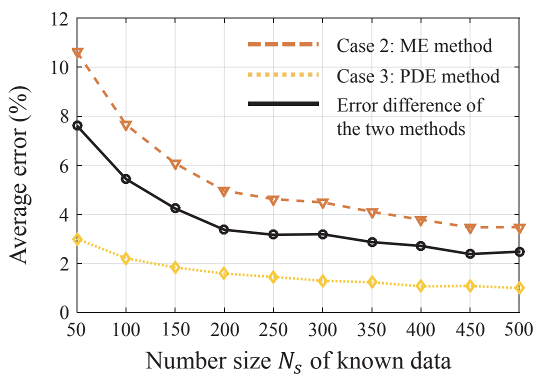

Fig. 9. Average error of ORC evaluation in different number size.

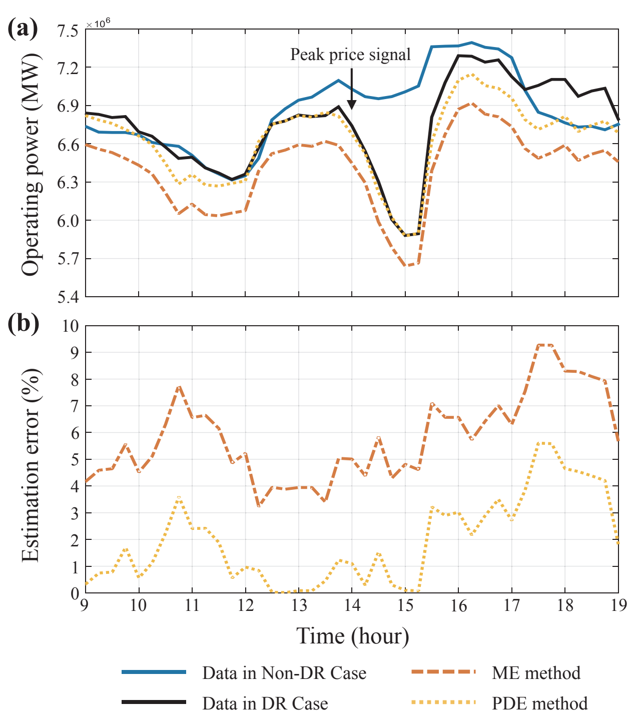

Fig. 10. Estimation of power consumption in DR program.

where $\widehat{P}_{ORC}^{m}$ is the evaluated ORC of the aggregated TCLs in Case m.

4.2. ORC evaluation with insufficient data

The first stage of the PDE method is to estimate the distribution of heterogeneous insufficient parameters by kernel density estimation. The accuracy of the proposed method is analyzed as shown in Fig. 7.

Fig. 7(a) and (b) show the probability density distributions of the thermal mass C_{room} and the thermal conductance H_r, respectively. Both known data points are marked with a number of tiny black bars scattered on the axis of the abscissa. Frequency histograms and kernel density are marked with the gray histograms and the red curves, respectively. As shown in the figures, frequency histograms of 100 TCLs can reflect the general trend of the actual density (the blue curve). But there are obvious deviations due to abnormal data, such as the third histogram in Fig. 7(a). By contrast, probability density of 100 TCLs estimated by PDE method is almost overlapped with the actual density distributions, which is able to reduce the impact of the abnormal data and smooth the curve. The joint density distribution is obtained from the probability densities of H_r and C_{room}, shown in Fig. 7(c).

Fig. 8 shows the ORC evaluation performances of different methods in different number size N_s of known data. When $N_s = 100$, compared with the curve of ME method (the red dotted curves), the curve of PDE method (the orange dotted curves) is much closer to the actual curve (the blue solid curves). The error comparison is shown in Fig. 8(d), where the errors reach over 9.0% in ME method, whereas the errors in PDE method are within 4.0%. Similar conclusions can be made in other values of N_s. Therefore, the proposed PDE method is more accurate than ME method, and is able to improve the ORC evaluation accuracy based on the same insufficient data.

Fig. 8(d)–(f) show the trend of evaluation errors of ME method and PDE method in different N_s, respectively. In comparison of the three figures, both errors of ME method and PDE method experience a significant decrease with the increase of N_s. More details of evaluation errors are explained in Fig. 9.

In Fig. 9, average errors corresponding to different number size N_s are calculated to highlight the PDE method applicability in different data distributions. With the increase of N_s, the average errors of both methods decline and converge to zero gradually. In comparison, the average error of PDE method is significantly less than that of ME method. The error differences of the two methods are shown in Fig. 8 (the black solid curve), where the maximum difference reaches 7.8% at

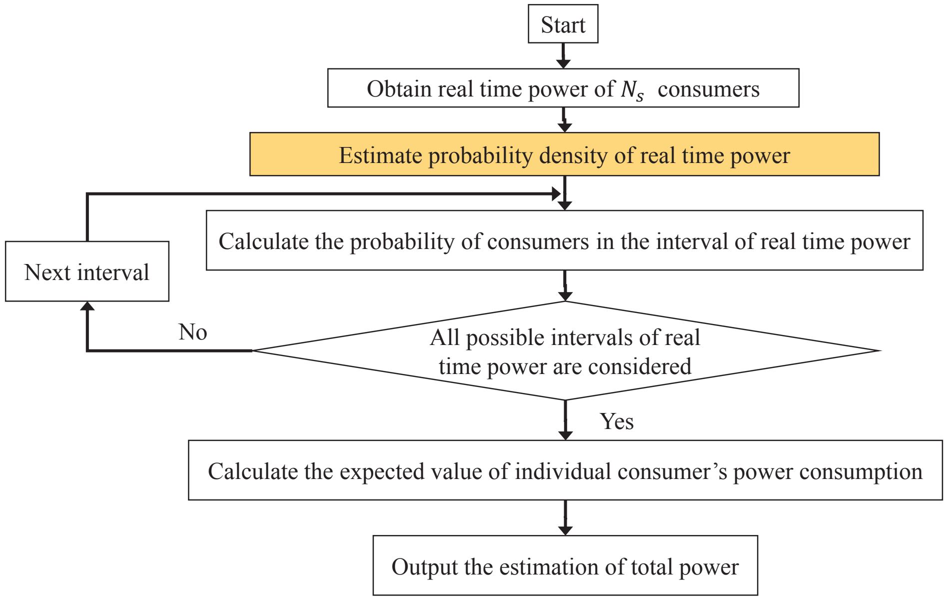

Fig. 11. The flow chart of estimation of power consumption.

the number size 50. The trend of curve shows that there are less error differences in larger number sizes, which highlights the estimation accuracy of PDE method especially in small number size of known data.

4.3. ORC evaluation in actual case studies

In this subsection, the practicality of the proposed PDE method is verified in the case studies based on actual DR data. Firstly, one of the pilot projects in a province of China is introduced with actual data. Then it is illustrated that the proposed PDE method can be applied in possible events of the pilot project. Finally, case study and analysis of PDE method applications are discussed.

4.3.1. Introduction of the pilot project

One of the pilot projects selects 522 residential consumers in Jiangsu province of China, where the power consumption of TCLs accounts for more than 30% during summer peak load. Smart meters and terminal controllers are installed in order to enable consumers to make demand response strategies with their personal needs.

The aggregated power consumption of selected consumers is collected in every 15 min for two weeks under similar weather conditions. The first week data without demand response (DR) program is regarded as baseline load. During the second week, the peak price signals were sent to consumers between 14:00 and 15:00 every day and thereby, the power consumption decreased to provide ORC for power system. The power consumptions are averaged based on the obtained data of the two week.

Results of actual DR program are shown in Fig. 10(a), where the blue solid curve is the sum of power in non-DR case, while the black solid curve is the sum of power in DR case. These two curves are overlapped at most of the time except for the period between 14:00 and 16:00, where the DR case experienced a significant load curtailment and the power consumption decreased to the minimum at 14:56. The operating reserve capacity (ORC) is 1.22 MW, calculated by the maximum load curtailment. It proves the feasibility of demand response providing operating reserve for power systems.

4.3.2. Case studies of proposed method applications

The proposed PDE method, which provides a more accurate estimation with less measured data, can be widely applied in demand response programs. For example, in the case of data loss due to communication or measurement failure, complete data of every individual cannot be obtained to calculate aggregated power consumption, which may serve as an important index for further actions. In the circumstances, the proposed PDE method provides an approach to improve the accuracy of estimation with limited available data, which could help to make the right decisions.

The following case study shows the application of PDE method in the above pilot project when there exists data loss. The total number of residential consumers is N in the pilot project. It is assumed that only the data of N_s consumers can be obtained while other data is lost due to equipment failures. The ME method and PDE method are applied to estimate the power consumption with N_s known consumers, respectively. N and N_s are set to be 522 and 50, respectively. The flow chart of this case studies is shown in Fig. 11.

Fig. 10(a) shows the estimation of power consumption with ME method and PDE method, which is illustrated by the red dotted curve and the orange dotted curve, respectively. The estimation of power consumption obtained by PDE method is much more consistent with that of ME method. The error between estimation data and actual data in DR program (the black solid curve) is shown in Fig. 10(b), where PDE method is more accurate and appropriate than ME method. The average error of ME method reaches 5.90%, which is relatively high value. Compared to that, the average error of PDE method is 2.52%, which is much less than that of ME method and thereby, proves the practicality of PDE method to estimate aggregated power with insufficient data.

5. Conclusions

The progress of information and communication technology has made it easier for demand side resources to provide operating reserve. This paper proposes a quantitative evaluation method of operating reserve capacity (ORC) provided by aggregated heterogeneous TCLs with insufficient measurement data. The individual TCL model considering consumer's behaviors is developed to characterize the impact of fluctuated electricity prices and different temperature requirements. Consumer's perspective on electricity prices and feeling of the room temperature are modeled by the fuzzy set method. In this manner, the consumer's satisfaction is defined and then optimized in the maximum satisfaction control strategies. Moreover, the probability density estimation (PDE) method is proposed to evaluate the ORC provided by large-scale heterogeneous TCLs without sufficient measurement data. The numerical studies shows that, compared with the traditional estimation method, the PDE method can improve the accuracy of the ORC evaluation with insufficient data.

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References

[1] Ma O, Alkadi N, Cappers P, Denholm P, Dudley J, Goli S, et al. Demand response for ancillary services. IEEE Trans Smart Grid 2013;4(4):1988–95.
[2] Wang J, Wang X, Wu Y. Operating reserve model in the power market. IEEE Trans Power System 2005;20(1):223–9.
[3] Hui H, Ding Y, Liu D, Lin Y, Song Y. Operating reserve evaluation of aggregated air conditioners. Appl Energy 2017;196:218–28.
[4] Bricman Rejc Z, Cepin M. Estimating the additional operating reserve in power systems with installed renewable energy sources. Int J Elect Power Energy Syst 2014;62:654–64.
[5] Siano P, Sarno D. Assessing the benefits of residential demand response in a real time distribution energy market. Appl Energy 2016;161:533–51.
[6] Hu J, Cao J, Chen ZM, Yu J, Yao J, Yang S, et al. Load following of multiple heterogeneous TCL aggregators by centralized control. IEEE Trans Power System 2017;32(4):3157–67.
[7] Zhang W, Lian J, Chang CY, Kalsi K. Aggregated modeling and control of air conditioning loads for demand response. IEEE Trans Power System 2013;28(4):4655–64.
[8] Hwang JC. Assessment of air condition load management by load survey in Taipower. IEEE Trans Power Syst 2001;16(4):910–5.
[9] Wang K, Yao J, Yao L, Yang S, Yong T. Survey of research on flexible loads scheduling technologies. Autom Elect Power Syst 2014;38(20):127–36.
[10] Callaway DS. Tapping the energy storage potential in electric loads to deliver load following and regulation with application to wind energy. Energy Convers Manage 2009;50(5):1389–400.
[11] Papadaskalopoulos D, Strbac G, Mancarella P, Aunedi M, Stanojevic V. Decentralized participation of flexible demand in electricity markets—Part II: application with electric vehicles and heat pump systems. IEEE Trans Power Syst 2013;28(4):3667–74.
[12] Dehghanpour K, Afsharnia S. Electrical demand side contribution to frequency control in power systems: a review on technical aspects. Renew Sustain Energy Rev 2015;41:1267–76.
[13] Lu N, Zhang Y. Design considerations of a centralized load controller using thermostatically controlled appliances for continuous regulation reserves. IEEE Trans Smart Grid 2013;4(2):914–21.
[14] Zheng ML, Fang RY, Yu ZT. Life cycle assessment of residential heating systems: a comparison of distributed and centralized systems. In: Applied Energy symposium and forum 2016: low carbon cities & urban energy systems. 2016.
[15] Luo F, Dong ZY, Meng K, Wen J, Wang H, Zhao J. An operational planning framework for large-scale thermostatically controlled load dispatch. IEEE Trans Indust Informatics 2017;13(1):217–27.
[16] Lu N. An evaluation of the HVAC load potential for providing load balacing service. IEEE Trans Smart Grid 2012;3(3):1263–70.
[17] Bianchini G, Casini M, Vicino A, Zarrilli D. Demand-response in building heating systems: a model predictive control approach. Appl Energy 2016;168:159–70.
[18] Liu M, Shi Y. Model predictive control of aggregated heterogeneous second-order thermostatically controlled loads for ancillary services. IEEE Trans Power Syst 2016;31(3):1963–71.
[19] He X, Keyaerts N, Azevedo I, Meeus L, Hancher L, Glachant JM. How to engage consumers in demand response: a contract perspective. Utilities Policy 2013;27:108–22.
[20] Qv D, Dong BB, Cao L, Ni L, Wang JJ, Shang RX, et al. An experimental and theoretical study on an injection-assisted air-conditioner using R32 in the refrigeration cycle. Appl Energy 2017;185:791–804.
[21] Yu R, Yang W, Rahardja S. A statistical demand-price model with its application in optimal real-time price. IEEE Trans Smart Grid 2012;3(4):1734–42.
[22] Chassin DP, Rondeau D. Aggregate modeling of fast-acting demand response and control under real-time pricing. Appl Energy 2016;181:288–98.
[23] Alibabaei N, Fung AS, Raahemifar K, Moghimi A. Effects of intelligent strategy planning models on residential HVAC system energy demand and cost during the heating and cooling seasons. Appl Energy 2016;185:29–43.
[24] Gu C, Yan X, Yan Z, Li F. Dynamic pricing for responsive demand to increase distribution network efficiency. Appl Energy 2017;205:236–43.
[25] Allcott H. Rethinking real-time electricity pricing. Resour Energy Econ 2011;33(4):820–42.
[26] Gomez JA, Anjos MF. Power capacity profile estimation for building heating and cooling in demand-side management. Appl Energy 2017;191:492–501.
[27] Morales JM. Point estimate schemes to solve the probabilistic power flow. Reliab Eng Syst Safety 2007;22(4):1594–601.
[28] Chao H. Price-responsive demand management for a smart grid world. Elect J 2010;23(1):7–20.
[29] Ihara S, Schweppe FC. Physically based modeling of cold load pickup. IEEE Trans Power App Syst 1981;100(9):4142–50.
[30] Bhattacharyya K, Crow ML. A fuzzy logic based approach to direct load control. IEEE Trans Power Syst 1996;11(2):708–14.
[31] Jang J-SR. ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans Syst Man Cybernet 1993;23(3):655–85.
[32] Takagi T, Sugeno M. Fuzzy identification of systems and its applications to modeling and control. IEEE Trans Syst Man Cybernet 1985;15(1):116–32.
[33] Persky J. Retrospectives: the ethology of homo economicus. J Econ Perspect 1995;9(2):221–31.
[34] Epanechnikov VA. Non-parametric estimation of a multivariate probability density. Theory Probab Appl 1969;14:153–8.
[35] Molina-García A, Kessler M, Fuentes JA, Gómez-Lázaro E. Probabilistic characterization of thermostatically controlled loads to model the impact of demand response programs. IEEE Trans Power System 2011;26(1):241–51.
[36] Bowman AW, Azzalini A. Applied smoothing techniques for data analysis. New York: Oxford University Press Inc.; 1997.