REGULATING POTENTIAL ASSESSMENT OF INDIVIDUAL ELECTRO-HEATING LOAD USING SIMILARITY-BASED SUPORT VECTOR MACHINE

by

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The power supply side regulating capability of the power grid is limited, and it is important to dig deep into the load side regulation capability. Electro-heating load is a time-shifting load with the characteristics of small thermal inertia, fast response, high controllability, etc. It has the potential to participate in active power dispatching and control the power grid. When the electro-heating load is working, the indoor temperature curve is affected by many factors. It has a similar influence characteristic quantity, and a similar temperature rise and fall process is exhibited in the temparature setted range. When using the traditional equivalent thermal parameter to evaluate, the outdoor temperature at the end of the warming up or cooling down process is unknown, so the regulating potential of individual electro-heating load cannot be accurately evaluated. Therefore, this paper proposes a similarity-based support vector machine single electro-heating regulating potential evaluation method, and compared with the traditional equivalent thermodynamic model, it shows that this method has higher evaluation accuracy.

Key words: *electro-heating load, similarity, regulating potential assessment, support vector machine*

Introduction

The continuous growth of power peak load and the intermittent integration of renewable energy such as wind energy and solar energy going into the power grid have brought serious consequences such as grid operation difficulties and abandoned wind and light [1]. In this situation, it is often difficult to meet the safe and economic operation of the power grid by means of power generation, such as primary frequency modulation, automatic generation control, and economic dispatching, and it is necessary to assist the load control means [2]. In addition, with the continuous improvement of wind turbine installed capacity, following by facing a serious problem of abandoning wind. In the heating season in the Sanbei area of China, the total load is insufficient and the thermal power unit is narrowed by the restraint regulating space of the heating conditions, which is the main cause of abandoning wind.

Currently, using electro-heating in the northeastern region of China has become a trend. According to statistics, in 2017, Changchun City, the cumulative installed capacity of electro-heating load is 290 MW, accounting for 3.08% of the city's heating capacity, and showing a rapidly developing trend. Assuming that electro-heating can be 10% of the time shift, time shifting time of one hour, then electro-heating excavable regulating capacity is

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29 MWh. When the electro-heating capacity is increased to 3000 MW, the regulation capacity is increased to 300 MWh, which is equivalent to the regulation capacity of two 300 MW thermal power units. It can be seen that the regulating potential of electro-heating load is huge, and the ability to excavate and adjust the electro-heating load has become an important issue. At present, most of the research work is to evaluate the regulating ability of electro-heating load in the macro, the literature [3] puts forward the energy-efficient motor model with user comfort constraints as the output boundary. Based on this, an aggregation with multiple energy-efficient motors is constructed, energy-efficient power plant optimal allocation model. Hui *et al.* [4] conducted a study on cluster temperature control load participating in low frequency load shedding. Lu [5] estimates the HVAC aggregate power output curve based on the outdoor temperature simulated average load curve. In [6], the SQ-based comfort control constraint control strategy is used to polymerize the heat pump unit and numerically simulate the 1000 heat pump units. The regulating potential of the single electro-heating load is the basis of its polymerization model, but it is rarely studied. Therefore, based on the experiments, this paper proposes a similarity-based support vestor machine (SVM) electro-heating regulating potential evaluation method to evaluate the regulating potential of individual electro-heating load.

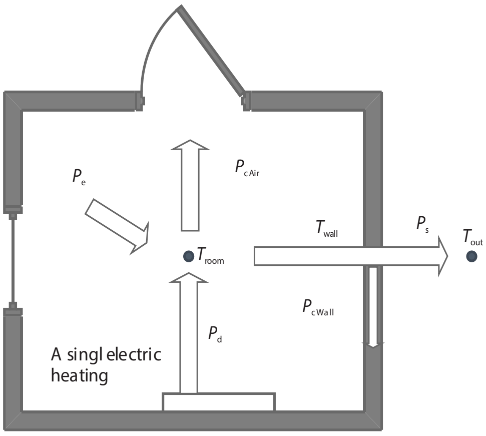

Figure 1. Energy conversion process of individual electro-heating load

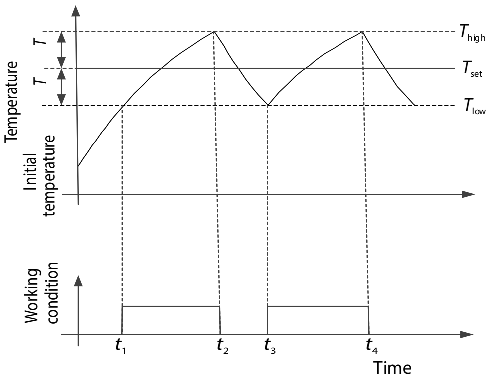

Figure 2. Dynamic process of individual electro-heating load

Modelling and experimentation of individual electro-heating load

Modelling of individual electrical heating load

When individual electro-heating work is carrying out, there is an energy conversion process between the indoor air and the building, the building wall and the outdoor air. The dynamic process of energy conversion is shown in fig. 1.

In the fig. 1, T_{room} is the indoor temperature, T_{out} – the outdoor temperature, T_{wall} – the wall temperature, P_d – the electro-heating heating power, P_e – the other thermal power, P_s – the outdoor heat dissipation, $P_{c\text{wall}}$ – the wall heat storage, and $P_{c\text{Air}}$ – to store heat to the air.

In the temperature control interval, the basic dynamic process of individual electro-heating work is shown in fig 2.

The indoor temperature fluctuates up and down around a certain temperature setting value T_{set}. When the temperature changes exceed a given upper temperature boundary, T_{high}, the switching state of the electro-heating device changes to *on* → *off*. When the temperature changes beyond the lower boundary, T_{low}, of the given temperature, the switch state of the electro-heating device changes to *off* → *on*, and the temperature varies within the upper and lower boundaries. The temperature rise process corresponds to power consumption, which means that electrical energy is converted into indoor heat energy. A drop in temperature means that the load is turned off, the temperature naturally drops, and the electrical power consumed is zero. Therefore, the product of the response time, h, of the electro-heating load in the temperature setting range [T_{high}, T_{low}] and the load power, kW, characterizes the regulating potential of the electro-heating load.

According to the previous analysis, individual electro-heating thermodynamic parameter model is established using the analog circuit method [7, 8], in which the voltage is analogous to temperature and the current is analogous to the heat flow, as shown in fig. 3.

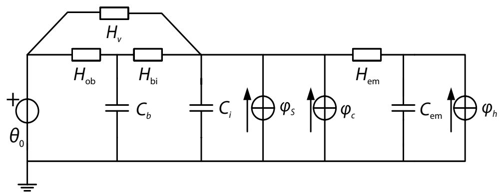

Figure 3. Thermal parameter model of electro-heating load

In fig. 3, θ_0 is the outdoor temperature H_v – the conductance is the indoor air ventilation heat loss, the value depends on the indoor air exchange rate, H_{ob} – the heat transfer coefficient between the outdoor air and the building wall, H_{bi} – the building wall and indoor air heat transfer coefficient, H_{em} – the heat transfer coefficient between electro-heating and indoor air, C_{b}, C_{i}, and C_{em} – the represent wall heat capacity, indoor air heat fusion, and electro-heating heat capacity, respectively, φ_s – the solar radiant heat gain, φ_{h} – *the* heating gain for electro-heating, and φ_{c} – the other heat gain.

After simplification, the previous thermodynamic parameter model can be used to approximate the indoor temperature changing process of electro-heating load by eq. (1) [9, 10]:

$$T_{\text{room}}^{t+1} = T_o^{t+1} + KQR - (KQR + T_o^{t+1} - T_{\text{room}}^{t})\,\text{e}^{-\frac{\Delta t}{RC}} \tag{1}$$

where T_{room} [°C] is the indoor temperature, C [J°C^{-1}] – the equivalent thermal capacitance, R [°CW^{-1}] – the equivalent thermal resistance, Q [W] – load electrical power, T_{o} [°C] – the outdoor ambient temperature, t – the simulation time, Δt – the simulation step size, K – the device switching state, when the device is turned on, $K = 1$, and when the device is turned off, $K = 0$.

From eq. (1), the equation for calculating the response time of electro-heating at the end of heating or cooling process:

$$\Delta t = -RC\ln\left(\frac{T_o^{t+1} + KQR - T_{\text{room}}^{t+1}}{T_o^{t+1} + KQR - T_{\text{room}}^{t}}\right) \tag{2}$$

Electro-heating experiment system

According to the aforementioned equivalent thermodynamic model (ETP) related parameters, the heating experiment of electro-heating load is carried out in Changchun City, and the data such as indoor temperature, outdoor temperature, switch state and time interval are collected. The 15th, 16th, and 17th floors of Building 3 are selected to simulate the heating environment of the bottom, middle and top floors, respectively. Two high-precision temperature recorders are installed in each room to record the room temperature and electric heater temperature, respectively. The two are placed to record the outdoor temperature in the south and north directions (positive and shaded), and the temperature recorder error is ±0.5 °C. The temperature recorder shows in fig. 4(a). As shown in fig, 4(b), the electro-heating equipment used in the experiment has the characteristics of fast heating rate, suitable for residential users, small businesses, office buildings*, etc.*, controlled by a thermostat.

Figure 4. Physical map of the experimental equipment; (a) temperature recorder, (b) electro-heating load

Regulating potential assessment of individual electro-heating load using similarity-based SVM

Factors of influencing similar selecting

When electro-heating load is working normally, the indoor temperature rise and fall temperature curve is affected by factors such as load switching state, outdoor temperature, indoor temperature upper and lower limits, and solar radiation. Therefore, the indoor temperature curve has the feature quantity such as the device switching state, the outdoor temperature, and the indoor temperature upper and lower limits. It is necessary to calculate the similarity of the curves for these several feature quantities, and select a similar lifting and lowering process as the training data of the SVM to perform the model. training and learning, in order to assess the potential of single electro-heating load regulating .

Similarity-based preprocessing

For the historical heating data,selecting recent days data as samples of similar selection, narrowing the range of similar choices. Assume that the characteristic value of the i^{th} temperature rise and fall process is $X_i = [x_{i1}, x_{i2}, x_{i3},\ldots,x_{im}]$, $i = 1, 2, 3,\ldots,$ m is the number of feature quantities. The feature quantity to be predicted is X_j, and the similarity r_{ij} between the historical time and the predicted time is calculated by the following eqaution, and the similarity equation can reasonably describe the similarity of the temperature change curve:

$$r_{ij} = \frac{\sum_{k=1}^{m}(X_{ik}X_{ik})}{\sqrt{\left(\sum_{k=1}^{m}X_{ik}^2\right)\left(\sum_{k=1}^{m}X_{jk}^2\right)}} \tag{3}$$

Equation (3) is a cluster-based analysis method [11], which can better measure the similarity of any two temperature-raising processes, and select data with similar similarity as model training samples.

The SVM theory

The SVM regression function used to estimate the basic idea is through a non-linear mapping, the mapping data of the input space to a high dimensional space, and then linear regression in this space. For the regression prediction problem, let the training sample x_i be the input vector, $x_i \in R^n$, y_i be the corresponding output value, $y_i \in R$, d_i is the expected value, $d_i \in$ R, $\{x_i, d_i\}$ is the training data, where $i = 1, 2, ..., n$, using the following regression function:

$$y = f(x) = w\varphi(x) + b \tag{4}$$

In eq. (4), $\varphi(x)$ is a non-linear mapping from the input space to the high dimensional feature space. The correlation coefficients w and b are estimated:

$$R(w) = \frac{c}{n}\sum_{i=1}^{n} L_i\left[d_i, w\varphi(x_i) + b\right] + \frac{1}{2}\|w\|^2 \tag{5}$$

where c is a penalty factor that determines the balance between empirical risk and regularization. To find the coefficients w and b, introduce the relaxation variables ξ_i and ξ_i^*:

$$R(w,\xi,\xi_i^*) = \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n}(\xi_i + \xi_i^*) \tag{6}$$

$$s.t.\begin{cases} w\varphi(x_i) + b_i - d_i \le \varepsilon + \xi_i^*, & \xi_i^* \ge 0 \\ d_i - w\varphi(x_i) - b_i \le \varepsilon + \xi_i, & \xi_i \ge 0 \end{cases} \tag{7}$$

Using the characteristics of the kernel function, introducing the Lagrangian multipliers α_i and α_i^*, we can simplify eq. (6) into a two-order optimization problem:

$$w = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)x_i \tag{8}$$

Substituting eq. (8) into eq. (6) yields the regression function:

$$f(x) = wx + b = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)K(x_i, x) + b \tag{9}$$

where $K(x_i, x)$ is a kernel function, and Gaussian kernel function is used in this paper.

The process of regulating potential assessment of individual electro-heating load using similarity-based SVM

In this paper, the sequence minimum optimization (SMO) method is used to obtain α_i, α_i^* and b, which decomposes the large-scale original problem into several small-scale sub-problems, and finds the solution of the original problem through iteration. The flow is shown in the following fig. 5.

The specific steps are:

Step 1. Enter historical data and use the similarity theory to perform data preprocessing to form training and test data sets with high similarity.

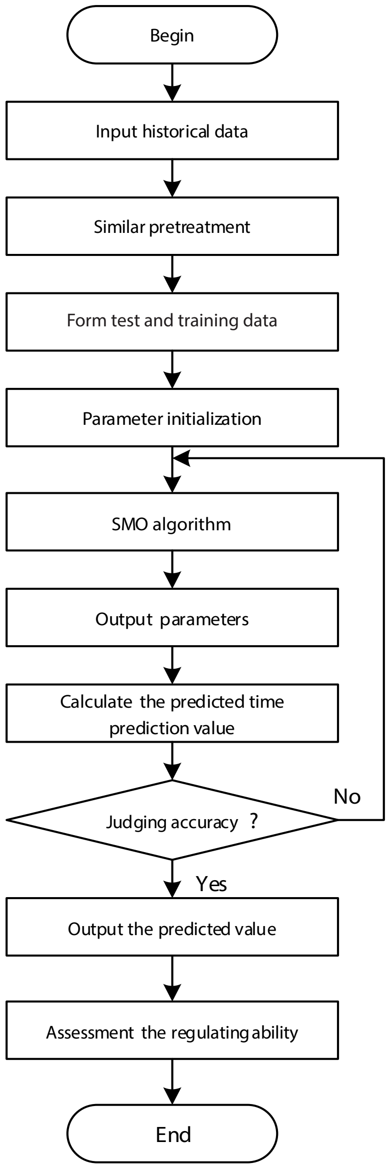

Figure 5. The SVM evaluation process based on similarity

Step 2. Initialize the SVM parameters and assign the Lagrangian multipliers α_i, α_i^*, and b to random initial values.

Step 3. Using the training data to establish the objective function shown in eq. (6), use the SVM algorithm to solve the objective function equation, and get α_i, α_i^* and b.

Step. 4 Substituting α_i, α_i^*, and b into eq. (9), and using the test data to calculate the predicted value at a certain moment in the future.

Step 5. Calculate the error function. When the absolute value of the error is less than a certain positive value preset, the learning process ends, otherwise it returns to *Step 3*.

Step 6. Evaluate the potential of individual electro-heating load regulation.

Study results and analysis

In order to reduce the impact of solar radiation, this study uses the 3rd floor of Kaiyunjiayuan Community, Changchun City, 1608 side (nightside), February 15th-17th, 2018 heating data, a total of 4320 datas, time resolution 1min, the power of electro-heating load power is 900 W, and the upper and lower limits of indoor temperature are 19-24 °C, and the simulation experiment is carried out.

Regulating potential assessment of individual electro-heating load using ETP

For the ETP modelling of individual electro-heating load, it is necessary to calculate the relevant parametric equivalent thermal resistance, R [°CW^{-1}], and the equivalent thermal capacitance, C [J°C^{-1}]. According to eq. (1), the fitting parameters can be obtained as shown in tab. 1. The fitting accuracy satisfies the requirements. Substituting the relevant parameters of the ETP model in tab. 1 into eq. (2), the response time Δt of the electro-heating load in the temperature setting range can be obtained, thereby evaluating the regulating potential of the current heating load.

Table 1. Values of related parameters of the ETP model

ETP parameter	R [°CW^{-1}]	C [J°C^{-1}]
Parameter value	0.1071	2171.7432

The ETP model parameters are fitted to the temperature curve of the 1608 side bedroom. The time is 2018/02/15 00:00:00-2018/02/17 19:58:00, a total of 4076 collection points, and some indoor temperature curves are shown in fig. 6. The corresponding relative error is shown in fig. 7.

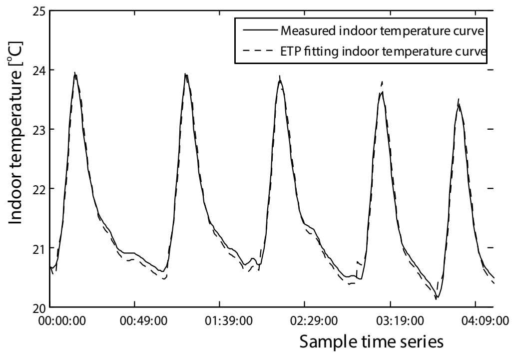

Figure 6. The ETP model fitting indoor temperature curve

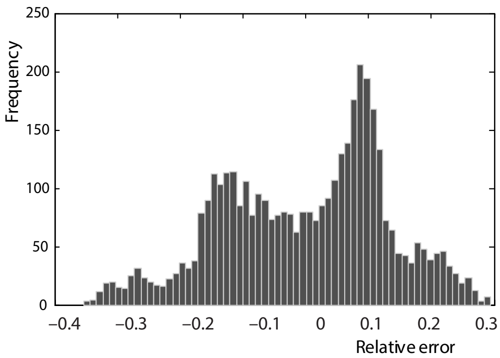

Figure 7. The ETP model fitting indoor temperature curve relative error

From the analysis of the indoor temperature relative error of the ETP model in fig. 7, the ETP fitting indoor temperature relative error is approximately concentrated in the interval [–0.1, 0.1], the maximum relative error is 0.375 °C, and the average error is 0.113 °C. According to the minimum value that human body can perceive the change of outdoor temperature, the model has good fitting accuracy.

Regulating potential assessment of individual electro-heating using similarity-based SVM

The similarity theory method is used to extract and predict the training data with similar timing. The feature quantity in the similar selection process is used as the input of SVM. The corresponding input quantity is current room temperature T_{room}, outdoor temperature T_{out}, temperature setting range [T_{high}, T_{low}], load power Q, and outdoor temperature change trend, when the outdoor temperature is rising, the value is 1. When the outdoor temperature is declining, the value is –1. The response time Δt of the electro-heating load in the temperature setting range is used as the output of the SVM to predict the response time of the electro-heating in the 20 predicted times, and then to evaluate the current regulating potential of the electro-heating, and to the traditional ETP comparison, as shown in figs. 8 and 9.

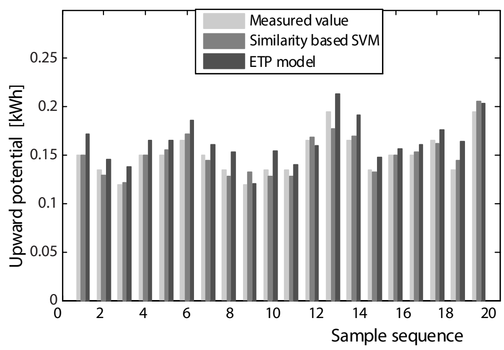

Figure 8. Comparison of the upside potential of the two methods

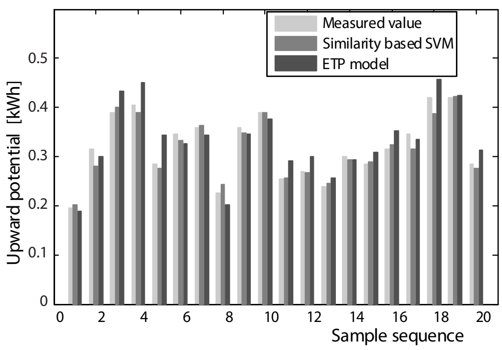

Figure 9. Comparison of the potential reduction of the two methods

In this paper, the relative average absolute percentage error (MAPE) and the maximum error (ME) are used as the evaluation criteria to analyze the prediction results. The MAPE and the ME:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_i - t_i'}{t_i}\right|100\% \tag{10}$$

$$ME = \left|t_i - t_i'\right| \tag{11}$$

where t_i and t_i' are the true value and the predicted value at the i^{th} time, respectively, n is the number of predicted times, $n = 20$.

The ETP model and the similarity SVM method error pair are shown in tab. 2. From the table, we can see the evaluation results of the similarity-based SVM method. The average MAPE of the up-regulation potential is 3.7806%, the maximum error is 0.0171 kWh, the average absolute percentage error of the down-regulation potential is 3.5268%. The maximum error is 0.0353 kWh, and the evaluation accuracy is higher than that of the traditional ETP model.

Therefore, the similarity-based SVM evaluation method can obtain better evaluation results and more accurately evaluate the regulating potential of individual electro-heating load.

Table 2. Comparison of the error between the two methods

Method	Up MAPE [%]	Down MAPE [%]	Up ME [kWh]	Down ME [kWh]
ETP	9.8767	7.8594	0.0290	0.0579
SVM	3.7806	3.5268	0.0171	0.0353

Conclusion

In this paper, the similarity theory is used to process the historical data, fully consider the change of indoor temperature during the operation of electro-heating load and the influence of outdoor temperature on the regulating potential of electro-heating, and select historical data with high similarity with the prediction time as the training sample. The evaluation accuracy of the electro-heating regulating potential is improved. Compared with the traditional equivalent thermodynamic model evaluation method, the similarity-based electro-heating regulating potential evaluation method obtains higher evaluation accuracy, and verifies its effect and practicality and laid the foundation for the next stage to evaluate the regulating potential of the polymerization model of electro-heating load. In the analysis of the example in this paper, the room with the shade is ignored, and the influence of other factors such as solar radiation on the regulating potential of electro-heating is ignored. The next model can consider more influencing factors to further improve the accuracy of the mode.

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