Research on Combined Forecasting of Cooling Load Based on Advanced Cuckoo Search and Improved Particle Swarm Optimization

Chenchen Zhang, Yilin Cong, Ye Tian, Anzhu Guo, Tao Liu and Yongzhi Ma*
School of Electromechanic Engineering, Qingdao University, Qingdao 266071, Shandong, China
*Corresponding author email: hiking@126.com

Abstract. This study aims to improve the real-time accuracy of cooling load forecasting for heating, ventilating and air-conditioning systems (HVAC). This article takes the cooling load in a study room in Qingdao, China, which has been put into use for the first time, as the research object, and establishes a TRNSYS simulation platform to obtain sufficient load data. After using the mean influence value (MIV) and Spearman correlation coefficient to screen the characteristic variables, a hybrid algorithm (CS-CPSO) based on cuckoo search (CS) and particle swarm optimization (PSO) is proposed. Firstly, the iterative extremum is introduced to PSO, secondly, mechanism of levy random flight to generate random new nest in CS is used to initialize PSO particles adaptively. Finally, the optimization algorithm is applied to optimize the back propagation (BP) and support vector regression (SVR) load training models (WBP, WSVR, RBP, RSVR) of the working day (W) and rest day (R), respectively. The maximum grey correlation coefficient is utilized to establish the both models (CS-CPSO-W, CS-CPSO-R) of the working day (W) and rest day (R) based on CS-CPSO. In this way, the forecasting results are optimized and then compared with the regression prediction method. The analysis shows that the accuracy of the optimized BP model and SVR model are improved and fully considering the differences, the accuracy of the cooling load prediction is effectively promoted by separately, optimal selection between the prediction values of advanced models (CS-CPSO-WBP, CS-CPSO-WSVR, CS-CPSO-RBP, CS-CPSO-RSVR) gives full play to each algorithm’s advantages and makes up for their shortcomings, and it greatly increases reliability and improves accuracy, which in turn provides the basis for the optimal plan, control, and operation of the HVAC.

1. Introduction
The increase in world energy demands has brought about a surge in energy consumption [1]. Building work accounts for about 30% of the world energy consumption [2] and is thus in better standing to reduce energy consumption than other sectors. Heating, ventilating and air-conditioning (HVAC) systems are responsible for the largest percentage of the building industry’s energy consumption [3] but they also have great potential to save energy by matching the energy supply with actual load demand [4]. Improving HVAC’s operating efficiency is therefore essential to reducing energy consumption. Accurate forecasting of the cooling load is of great significance in this mission [5]. Cooling load forecasting refers to the short-term prediction of the cooling capacity required by the air-conditioning system during future building operations. The three methods used for load forecasting are: physics-based approach, parametric model approach, and non-parametric model approach. Physical modelling uses the heat transfer mechanism to build the load through the simulation platform [6, 7], such as Energy Plus [8]. However, the physical model cannot guarantee a real-time performance [9],
and so is not commonly used [4]. The parametric model approach is a method whereby a mathematical model or statistical model is established based on the relationship between the analysis’ influencing factors and the cooling load, which mainly includes statistical regression [10] and time series. Statistical regression consists in a parameter model algorithm with a clear and simple algorithm and fast calculation speed. However, a large workload is needed to obtain it. The time series approach is a method that extrapolates the historical load alongside a statistical analysis, the Auto Regressive model (AR), the Moving Average model (MA), the Autoregressive Moving Average model (ARMA) and the Autoregressive Integrated Moving Average model (ARIMA), in order to forecast the future cooling load [11]. It can be simply used for modelling, but is only suitable for forecasting systems that have uniform load changes [12]. The nonparametric approach has attracted lots of attention due to its combination with intelligent algorithms, which includes decision trees [13], grey forecasting [14], the genetic algorithm (GA) [15], and the intelligence algorithm [16]. The characteristics of the decision tree include being multi branch, a directed and acyclic tree, and being highly efficient and only requiring a small amount of calculation. However, it does not cope well with either time series or nonlinear data [13], and its prediction results often significantly deviate from the actual situations [17]. The grey approach obtains relatively more accurate prediction results than the statistical analysis when there are fewer training parameters, but for a building load with strong randomness and large dispersion, its prediction accuracy cannot meet the requirements [18]. The genetic algorithm obtains an approximate optimal solution through selection, crossover and mutation, but its operation is complex, its result is not unique, and its algorithm time is longer than that of particle swarm optimization. Usually, the cooling load data series always exhibit nonlinear and dynamic features [19]. The artificial intelligence algorithm shows good characteristics when dealing with complex nonlinear problems, such as those posed by the support vector machine (SVM) [20] or the artificial neural network (ANN) [21]. The support vector machine was proposed on the basis of statistical theory, and consists of a kind of approximate realization algorithm of structural risk minimization (optimizing structural risk to minimize). It is also a common intelligent algorithm [22] and is good at solving dimension disasters and local minimum problems. The most common neural networks are the convolutional neural network (CNN), radial basis function (RBF) and back propagation (BP) neural network. Among them, the BP neural network is widely used for load prediction due to its strong nonlinear mapping, self-learning, generalization and fault-tolerant abilities [23]. Chou et al. [24] modelled their air conditioning load using SVR, ANN, a classification and regression tree, chi-squared automatic interaction detector, and general linear regression. Ma et al. [25] presents the SVM method to forecast China’s building industry’s energy consumption and the proposed model’s performance is then checked by comparing the prediction model with statistical data taken from the Chinese National Bureau of Statistics across 30 of China’s provinces (including autonomous regions and municipalities). Li et al. [26] modelled a SVM to forecast the hourly cooling load, and then applied it to an office building in Guangzhou, China. The results showed that this is an effective cooling load forecasting method. Zhang et al. [27] selected similar daily load data and key meteorological factors as the input for the BP network. The results showed that this model is very practical. In order to further optimize the algorithm, improve the accuracy and converge faster however, many scholars have tried to optimize the BP and SVR parameters. Zhang, Wang et al. [28] discuss using particle swarm optimization (PSO) to optimize the SVM’s thermal load forecasting model. Zhang et al. [29] presented the Dragonfly Algorithm-based support vector machine (DA-SVM) method to forecast the short-term load in microgrids. Li [30] applied BP based on an improved fruit fly optimization algorithm (IFOA-BP) to load forecasting. Among many optimization algorithms, Li et al. [31] was able to establish a new adaptive short-term load forecasting model by using an adaptive PSO-SVM method. The simulation results showed that the adaptive PSO-SVM method has a high prediction accuracy, strong generalization ability and strong feasibility. Lin et al. [32] combined the least-square support vector machine (LSSVM) and particle swarm optimization (PSO) and checked their convergence and performance. For the sake of satisfying accuracy requirements, Bui et al. [33] set up a genetic algorithm (GA) and imperialist competition algorithm (ICA) to optimize the weights and biases of the artificial neural network (ANN) in the estimation of the heating load (HL) and cooling load (CL) of the energy-efficient residential buildings. This type of combination forecasting research is gradually
gaining more traction. Various combined prediction methods have achieved good prediction accuracy. However, there are very few combined forecasting methods used to predict the cooling load of self-study rooms. Most existing research is aimed at either office or residential buildings. Due to the many different types and uses for buildings, there are great differences in occupant behaviour [34]. The remainder of this article is arranged as follows: Section 2 introduces the data source and preprocessing. Section 3 describes the machine learning approach to formulation and predictive techniques. Section 4 presents a simulation, analysis and comparison of the predictive results from different algorithms. Section 5 concludes the paper.

2. Data Preprocessing

Table 1 shows the parameters setting of dynamic hourly load simulation based on TRNSYS dynamic simulation platform.

| Parameter          | Working days | Rest days |
|--------------------|--------------|-----------|
| Number of people per hour |              |           |
| Working days       | 6:00-23:00   | 0:00-9:00 |
| Rest days          | 9:00-22:00   | 9:00-11:00|
| Lighting/ (w/m²)   | 10           | 0         |
| Fresh air volume/ m³/person | 25          | 0         |

3. CS-CPSO Theory

3.1 CS Algorithm

CS algorithm generates random solution through Levy flight [35]:

$$L(\kappa) \sim \frac{r_1}{|r_2|^{1/\kappa}} \left( \frac{\Gamma(\kappa+1)\sin(\frac{\pi \kappa}{2})}{\Gamma(\frac{\pi \kappa}{2})\kappa 2^{\kappa^2/2}} \right)^{1/\kappa}$$

The parameter $\kappa$ is 1.5, $r_1, r_2, r_3$ are standard Gaussian random numbers, $\Gamma(\bullet)$ is the gamma function. The new nest is obtained by the difference between the current iteration value and the optimal solution:

$$nest_{new} = nest + r_3 0.01 L(\kappa)(nest_{current} - nest_{best})$$

(1)

(2)
3.2 CPSO Algorithm

The standard PSO algorithm does not take into account the exchange of information with other particles during the flight of the particles, does not make full use of the exchange information in the iterative process, improved particle swarm velocity update formula is shown in formula 3:

$$v^j_i = wv^{j-1}_i + c_1 \alpha_i ((1-\alpha')(g^{j-1}_i-x^{j-1}_i) + \alpha'(cbest^{j-1} - x^{j-1}_i))$$

$$+ c_2 r_2(z^{j-1}_i - x^{j-1}_i)$$

(3)

Where: $cbest^j$ is best position of all particles between iteration $j$ and $j-1$, which strengthens the ability of information sharing in the iterative process, and prevents the particle diversity from disappearing in the later stage.

3.3 CS-CPSO

The standard PSO algorithm has a slow convergence speed and is prone to being premature and local optimization. The mechanism of using levy to reinitialize some particles provides a new random direction of flight, and avoids the risk of flying beyond the search space at the same time. The modeling process of CS-CPSO-BP and CS-CPSO-SVR is shown in figure 1.

![Modelling process of optimized algorithm](image)

Figure 1. Modelling process of optimized algorithm

3.4 Combined Algorithm

Combined forecast can effectively extract the most effective information from a single forecasting model and combine the advantages of the forecast results of various algorithms. This paper proposes to use the larger grey correlation coefficient in order to combine two single models together. Supposing that the system characteristic data sequence is $X_i^{(0)}(0)$, and the sequence of influencing factor is $X_i^{(0)}(t)$, $t = 1, 2, \ldots, m$, the grey correlation coefficient $\xi$ is as follows:

$$\xi = \frac{\min \min \left| X_i^{(0)}(t) - X_i^{(0)}(0) \right| + \rho \max \max \left| X_i^{(0)}(t) - X_i^{(0)}(0) \right|}{\left| X^{(0)}(t) - X_i^{(0)}(0) \right| + \rho \max \max \left| X_i^{(0)}(t) - X_i^{(0)}(0) \right|}$$

(4)

The predicted load value at the larger gray scale correlation coefficient in the two single models is extracted as the final predicted value $y_i$. It is shown in formula 5.

$$y_i = y_i \left[ \xi = \max(\xi(1), \xi(2), \ldots, \xi(m)) \right]$$

(5)
The maximum grey correlation coefficient couples each algorithm’s results to obtain higher forecasting accuracy. This paper’s algorithm flow is shown in figure 2.

**Figure 2. Modelling process**

4. Verification and Analysis
Solar radiation (SR): SR(t-3), SR(t-4); People (P): P(t); Temperature(T): T(t), T(t-24), T(t-48); Relative humidity(H): RH(t); Fresh air volume (FAV): FAV(t); Wind speed (WS): WS(t); Historical cooling load (HCL): HCL(t-1), HCL(t-24) are selected as input variables. Considering that graduate students leave school during the summer vacation, the simulation cooling load’s time range in this paper is set from May 15 to August 15, 15357 groups of data and the time step is set to 10 minutes. It is shown in figure 3 (a). In order to improve training speed and efficiency, the non-operating time data of the air conditioning equipment is deleted; a total of 8814 sets of data. Then the last week is taken as the verification test set, a total of 678 sets of data, and the remaining data is the training data. It can be seen from figure 3 (b) that the load distribution of working days and rest days is quite different. Therefore, modelling separately according to the load distribution characteristics not only improves the prediction accuracy, but also makes the prediction model more personalized.

**Figure 3. Dynamic cooling load**

(a)                                                                            (b)
Three methods are used to improve the forecasting accuracy. Method 1: modelling separately according to the difference of load distribution. Method 2: optimizing the model parameters by using the proposed intelligent algorithm. Method 3: combining the forecasting models with the maximum grey correlation coefficient. The performance of the models modelled separately is shown in table 2.

### Table 2. Performance of each model

| Model       | RMSE/ (kW) | MAE/ (kW) | MAPE/ (%) | CV/ (%) | R²  |
|-------------|------------|-----------|-----------|---------|-----|
| BP<sub>w</sub> (model 1) | 0.3839 | 0.2015 | 1.3898 | 0.0264 | 0.9936 |
| BP<sub>r</sub> (model 1) | 0.2898 | 0.1608 | 1.5482 | 0.0234 | 0.9952 |
| SVR<sub>w</sub> (model 2) | 2.2526 | 1.8077 | 15.8421 | 0.1454 | 0.8743 |
| SVR<sub>r</sub> (model 2) | 1.2942 | 1.0593 | 14.3033 | 0.1673 | 0.5723 |
| W<sub>BP</sub> (model 3) | 0.2970 | 0.1614 | 1.0538 | 0.0192 | 0.9945 |
| R<sub>BP</sub> (model 4) | 0.2075 | 0.1323 | 1.8759 | 0.0268 | 0.9865 |
| W<sub>SVR</sub> (model 5) | 2.1020 | 1.7345 | 14.0263 | 0.1357 | 0.8726 |
| R<sub>SVR</sub> (model 6) | 1.4371 | 1.0685 | 14.6966 | 0.1857 | 0.5141 |

BP<sub>w</sub> and BP<sub>r</sub> are respectively the forecasting values of working time and rest time in the same BP network. SVR<sub>w</sub> and SVR<sub>r</sub> are respectively the forecasting values of working time and rest time in the same SVR. W<sub>BP</sub>, W<sub>SVR</sub> are BP and SVR forecasting models of working time respectively. Similarly, R<sub>BP</sub>, R<sub>SVR</sub> are BP and SVR forecasting models of rest time. The above table shows that when considering the difference in load variation trends, the predictive load error obtained when considering modelling training separately is lower, the predictive level is better. However, the error is still big. The performance of each model optimized by method 2 is shown in figure 4, figure 5.

![Figure 4](image_url)  
**Figure 4.** Comparison of optimized model (working day).
It can be seen that the BP forecasting models optimized by CS-CPSO (model 8, model 12) perform better than those optimized by PSO (model 7, model 11) respectively. Similarly, the predictive error found in SVR optimized by CS-CPSO (model 10, model 14) are smaller than in those optimized by PSO (model 9, model 13) respectively. However, there are still peak values in the error series in figure 4 and figure 5, which indicates that there are predictive values that deviate significantly from targets. Combined forecast can extract the most effective information from each model and discard the useless. Method 3 is adopted to combine the optimal models and is compared with linear combined method.

![Figure 5. Comparison of optimized model (rest day).](image)

![Figure 6. Comparison between optimized models and combined models.](image)
Figure 6 (a, b) shows that the error sequence of the combined forecasting models (model 15, model 17, model 16, model 18) have significantly fewer singularities than that of the optimized models (model 8, model 10, model 12 model 14), both for the forecast of working days and for the forecast of rest days. From figure 6(c), we can more intuitively compare the performance of optimized forecasting models (7, 8, 9, 10) and combined forecasting models (15, 17) of working time. The combined forecasting model based on the maximum grey correlation (model 17) better than the linear combined forecasting model (model 15), model 15 is better than each optimal model and its error values are smaller and the error series is smoother, which shows that the predictive accuracy is improved and the random error basically disappears. The same conclusion can be drawn from figure 6 (d): model 18 is superior to model 16, and model 16 is superior to others. Table 3 also confirms those.

### Table 3. Comparison between optimized model and combined model

| Model | RMSE/ (kW) | MAE/ (kW) | MAPE/ (%) | CV/ (%) | R² |
|-------|------------|-----------|----------|--------|----|
| PSO-WBP (model 7) | 0.1669 | 0.0955 | 0.6178 | 1.0772 | 0.9982 |
| CS-CPSO-WBP (model 8) | 0.1071 | 0.0688 | 0.4682 | 0.69166 | 0.9993 |
| PSO-WSVR (model 9) | 0.2260 | 0.1181 | 0.8027 | 1.4592 | 0.9967 |
| CS-CPSO-WSVR (model 10) | 0.1328 | 0.1112 | 0.7677 | 0.8578 | 0.9989 |
| PSO-RBP (model 11) | 0.1813 | 0.1065 | 1.5327 | 2.3435 | 0.9887 |
| CS-CPSO-RBP (model 12) | 0.0568 | 0.0359 | 0.4912 | 0.7337 | 0.9988 |
| PSO-RSVR (model 13) | 0.1916 | 0.1725 | 2.3896 | 2.4769 | 0.9882 |
| CS-CPSO-RSVR (model 14) | 0.0948 | 0.0802 | 1.1161 | 1.2249 | 0.9967 |
| PSO-RW (model 15) | 0.0774 | 0.0521 | 0.3535 | 0.4997 | 0.9996 |
| CS-CPSO-RW (model 16) | 0.0415 | 0.0285 | 0.3970 | 0.53685 | 0.9994 |
| PSO-RW (model 17) | 0.0991 | 0.0690 | 0.46805 | 0.6399 | 0.9994 |
| CS-CPSO-RW (model 18) | 0.0537 | 0.0387 | 0.52351 | 0.6945 | 0.9989 |

5. Conclusion
- This paper fully considers the differences in load distribution between working hours and non-working hours. The accuracy of the algorithm is effectively improved by modelling the two separately.
- The particle swarm optimization is improved by introducing cuckoo search and the current iterative extreme value. Multiple evaluation indicators show that this improved algorithm is significantly better than the standard particle swarm algorithm.
- In order to satisfy the actual engineering requirement for high accuracy in complex and diverse environments, and further reduce errors, the maximum grey correlation coefficient was proposed to combine the BP neural network model and SVR model, to thus select the load forecast at the maximum grey correlation coefficient as the final value.

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