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Research on Load Forecasting based on Optimized Support Vector Machine Model

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Abstract

Accurate prediction of building energy consumption plays a vital role in energy scheduling, conservation, and emission reduction. However, conventional forecasting methods often struggle to capture nonlinear patterns effectively, leading to limited prediction accuracy. Focusing on rural residential buildings in Beijing, this study develops a Support Vector Machine (SVM) model based on measured data, and introduces Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to optimize the model's hyperparameters. The results demonstrate that the traditional SVM model achieves a coefficient of determination (R^2) of only 72.3%, with a mean absolute percentage error (MAPE) of 9.27% and a root mean square error (RMSE) of 0.92 kW. After optimization, the GA-SVM and PSO-SVM models significantly outperform the baseline: their R^2 values increase to 85.6% and 92.7%, respectively, while MAPE is reduced by 3.85 and 6.02 percentage points, and RMSE decreases by 0.39 kW and 0.53 kW, respectively. The findings underscore the effectiveness of optimization algorithms in enhancing SVM-based load forecasting and provide a reliable reference for energy management in similar building contexts.

Keywords

Support Vector Machine Model; Genetic Algorithm; Particle Swarm Optimization; Load Forecasting.

1. Introduction

In the global context of carbon emission reduction, energy management in the building sector has emerged as a critical issue. Statistics indicate that energy consumption in this sector accounts for over 40% of global final energy use [1]. Addressing this challenge, the international community has reached a consensus on the necessity of exploiting energy-saving potentials in buildings through refined control strategies. Within this framework, building load forecasting serves as a fundamental tool, providing decision support for the optimal dispatch of energy systems. By ensuring occupant comfort while effectively curbing unnecessary energy waste, it has become one of the core technologies for achieving carbon neutrality in the building sector [2].

SVM, grounded in the principle of structural risk minimization, constructs prediction models by leveraging kernel functions to map nonlinear problems in low-dimensional space to high-dimensional feature spaces for linear solutions. This model exhibits excellent generalization capability and robustness under limited sample conditions [3]. With its favorable balance in handling high-dimensional data, small-sample learning, and nonlinear relationship fitting, SVM has been extensively studied by researchers in the field of load forecasting.

Shi et al. [4] developed a short-term SVM model for thermal load forecasting and investigated the impacts of different feature combinations and time steps on model prediction performance. Azita et

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al. [5] employed SVM models to estimate the average errors in predicted power and heat consumption over a six-month period. Aasim et al. [6] proposed a novel SVM model based on repeated wavelet transform for day-ahead electricity load forecasting. Wei et al. [7] applied SVM models to train and predict heating loads in residential areas served by centralized energy supply systems.

Given the relatively simple structure of standalone SVM models, this study introduces GA and PSO to optimize the SVM model for enhanced building load forecasting accuracy. Based on this optimization, building load predictions are conducted, aiming to provide reliable data support for clean energy planning.

2. Experimental Study in Northern Rural Areas

2.1 Description of the Rural Residence

The data utilized in this study are derived from an authentic engineering project. The residential building was completed in 2005, with a total floor area of approximately 120 m². The indoor area dedicated to space heating accounts for 80% of the total building area.

2.2 Experimental Scheme and Data Acquisition

Fig.1 presents the schematic diagram of the heating system driven by an air-source heat pump and the corresponding data acquisition system. The experimental dataset covers the period from December 3 to December 30, 2019.

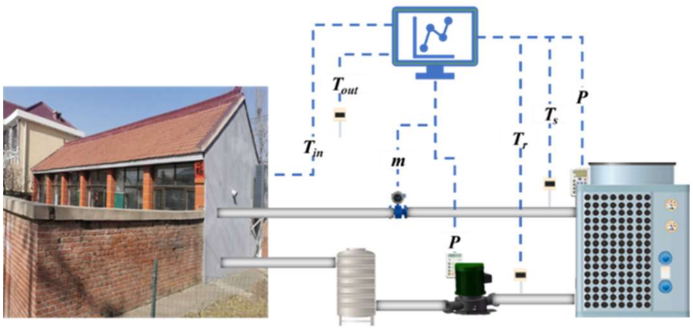

Fig.1 Schematic diagram of the air-source heat pump driven heating system and its data acquisition system

3. Building Load Forecasting Models

3.1 SVM Model

SVM is regarded as a machine learning method for regression prediction by seeking an optimal hyperplane. Kernel functions are employed to map data into a high-dimensional space when complex data are processed. In this way, nonlinear problems can be effectively solved. However, its predictive performance is highly dependent on the selection of key parameters.

3.2 GA-SVM Model

GA-SVM model is inspired by the "survival of the fittest" mechanism observed in biological evolution. Selection, crossover, and mutation operations are iteratively performed to automatically search for the optimal parameters of the SVM model. As a result, the blindness associated with manual parameter tuning is effectively avoided, and the prediction accuracy is significantly improved.

3.3 PSO-SVM Model

PSO-SVM model is designed by mimicking the foraging behavior of bird flocks. Information sharing and collaboration among individuals in the swarm are utilized to continuously adjust the search direction. Through this mechanism, the optimal combination of SVM parameters is rapidly identified, and the prediction performance of the model is significantly enhanced.

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3.4 Evaluation Metrics for Prediction Models

Evaluation metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) are employed to measure the accuracy of the models' parameter predictions.

4. Results and Discissions

4.1 Load Forecasting Using SVM Model

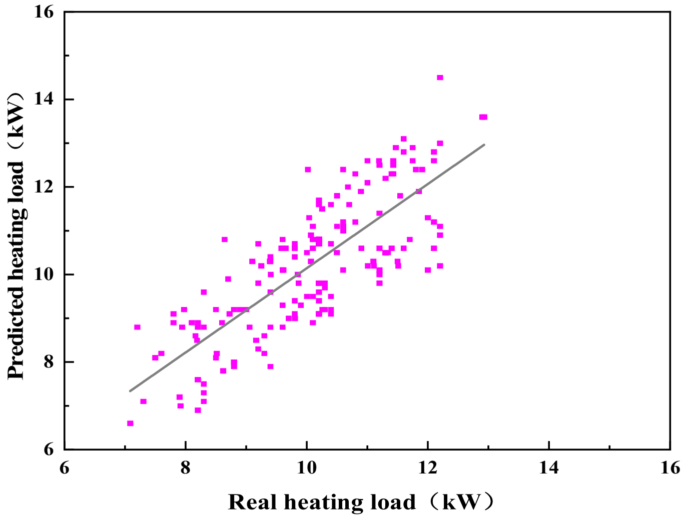

Fig.2 Linear regression analysis of the real and predicted heating load values of SVM model

Fig. 2 presents the linear regression analysis of the measured and predicted hourly load values. Based on the test dataset, MAPE, RMSE, and R^2 for the load forecasting are calculated as 9.27%, 0.92 kW, and 72.3%, respectively. A comprehensive analysis of Fig.2 and the evaluation metrics reveals that the predicted load values obtained from the SVM model generally follow the trend of the measured data; however, certain deviations in prediction accuracy are still observed.

4.2 Load Forecasting Using GA-SVM Model

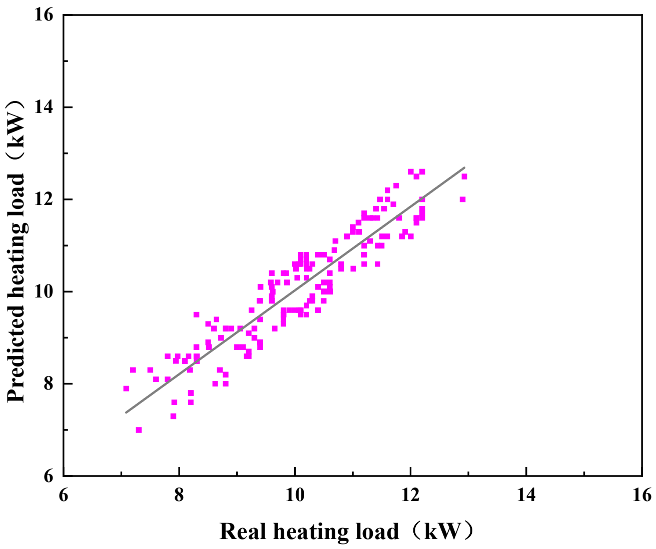

Fig.3 Linear regression analysis of the real and predicted heating load values of GA-SVM model

Fig.3 illustrates the correlation analysis between the measured and predicted load values using the linear regression method. Based on the test dataset, the prediction performance metrics of the optimized model are calculated as follows: MAPE is 5.42%, RMSE is 0.53 kW, and R^2 reaches 85.6%.

Compared to the traditional SVM model, the GA-SVM model, which optimizes the network weights and thresholds through the Genetic Algorithm, achieves a reduction in MAPE and RMSE by 3.85% and 0.39 kW, respectively, while the R^2 is improved by 13.3%.

4.3 Load Forecasting using PSO-SVM Model

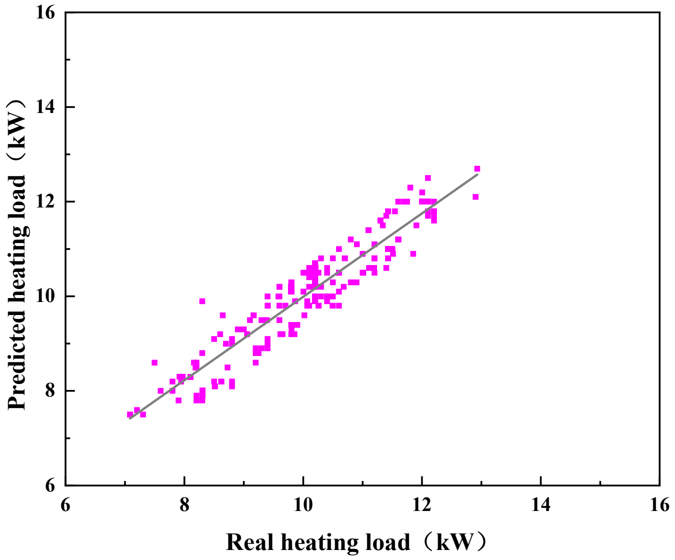

Fig.4 Linear regression analysis of the real and predicted heating load values of PSO-SVM model

Fig.4 presents the correlation analysis between the measured and predicted building thermal load values using the linear regression method. Based on the test dataset, the prediction performance of the PSO-SVM model is significantly enhanced, with MAPE of 3.25%, RMSE of 0.39 kW, and R^2 of 92.7%. Compared to the original SVM model, the MAPE and RMSE of the PSO-SVM model are reduced by 6.02% and 0.53 kW, respectively, while the R^2 is improved by 20.4%.

5. Conclusion

This study focused on a rural residential building in Beijing, and a prediction system based on the traditional SVM, GA-SVM, and PSO-SVM models was developed. Through comparative experiments and engineering validation, the main conclusions are drawn as follows:

(1) Compared with the traditional SVM model, the MAPE and RMSE of the GA-SVM model were reduced by 3.85% and 0.39 kW, respectively, while the R^2 was improved by 13.3%.

(2) The performance of the PSO-SVM model was further optimized. Its MAPE and RMSE were reduced by 6.02% and 0.53 kW, respectively, compared with the traditional model, and its R^2 reached 92.7%, which is 7.1% higher than that of the GA-SVM model, demonstrating superior nonlinear fitting capability.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Y. Gao, Y. Mastsunami, S. Miyata, et al. Model Predictive Control of a Building Renewable Energy System Based on a Long Short-Term Hybrid Model. Sustainable Cities and Society, 2023, 89: 104317.

[2] L. G. Kang, J. Z. Wang, X. X. Yuan, et al. Research on Energy Management of Integrated Energy System Coupled with Organic Rankine Cycle and Power to Gas. Energy Conversion and Management, 2023, 287: 117117.

[3] W. H. An, B. Gao, J. H. Liu, et al. Predicting hourly heating load in residential buildings using a hybrid SSA–CNN–SVM approach. Case Studies in Thermal Engineering, 2024,59:104516.

[4] Z. K. Shi, R.F. Zheng, R.D. Shen, et al. Building heating load forecasting based on the theory of transient heat transfer and deep learning. Energy and Buildings,2024,313:114290.

[5] A. Morteza, A. A. Yahyaeian, M. Marzieh, et al. Deep learning hyperparameter optimization: Application to electricity and heat demand prediction for buildings. Energy and Buildings,2023,289:113036.

[6] Aasim, S.N. Singh, A. Mohapatra. Data driven day-ahead electrical load forecasting through repeated wavelet transform assisted SVM model. Applied Soft Computing,2021,111:117730.

[7] Z.Q. Wei, T.W. Zhang, B. Yue, et al. Prediction of residential district heating load based on machine learning: A case study. Energy, 2021,231:120950.