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Intelligent forecasting of electricity consumption for hospital outpatient buildings by FOA-SVR hybrid strategy

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Introduction: To address the dilemma that the small sample size of hospital energy consumption data makes it difficult to predict short-term electricity consumption, a combination of the Firefly Optimization Algorithm (FOA) and the Support Vector Regression (SVR) algorithm, i.e., FOA-SVR, was proposed in this work.

Methods: By combining standardized sample data with the FOA to optimize the hyperparameters of the SVR model, the proposed approach enhances the model's ability to capture the variation characteristics of hospital electricity consumption.

Results: The FOA-SVR hybrid strategy achieves an optimal balance between prediction accuracy and computational efficiency when the number of fireflies was 30. The prediction accuracy indicator (Coefficient of Determination, R^2) was 0.855, respectively. Under these conditions, the hybrid strategy has the dual advantage of running faster than the existing Sparrow search algorithm, and the traditional seagull optimization algorithm, with run times reduced by 21.192 s and 14.612 s, respectively. When the length of electricity consumption data was greater than or equal to 36, R^2 of the FOA-SVR hybrid strategy was higher than 0.849.

Discussion: The FOA-SVR hybrid strategy realizes a kind of efficient prediction of power consumption in medical office buildings with a small sample data volume, which provides theoretical and data support for the reasonable optimization of hospital energy use structure and has practical significance for the intelligence of hospital energy management.

KEYWORDS

firefly optimization algorithm, support vector regression, small sample size, electricity consumption projections, hospital outpatient building

1 Introduction

In modern society, hospitals, as important public service facilities, were concerned about their energy consumption (Mazzeo et al., 2023; Roletto et al., 2024; Patil and Kini, 2024; Ghoreishinejad et al., 2023). Especially in outpatient clinic buildings, power consumption was usually high and unstable due to high patient turnover, irregular equipment working hours and extensive use of energy-consuming equipment such

as air conditioners. In addition, the seasonal character of electricity consumption in outpatient buildings was brought about by climatic variations in different seasons (Liu et al., 2022). Effective prediction of power consumption in hospital outpatient buildings not only helps to improve energy efficiency and reduce operating costs, but also helps hospital managers to optimize the power plan and ensure the stability and security of energy supply (Seçkiner and Koç, 2022; Soyler and Izgi, 2022; Cygańska and Kludacz-Alessandri, 2021).

The complexity of time series was an important theme in the available reports (Ponce-Flores et al., 2020). Time series data were affected by a combination of environmental factors and were often characterized by non-linearity (Wang et al., 2023; Satapathy et al., 2024). The complexity of time series features was brought about by nonlinear features (Wu et al., 2024). Econometric, statistical and mathematical methods as traditional forecasting methods have low forecasting accuracy in terms of their inability to better identify non-linear features in electricity consumption data (Khan et al., 2020). Machine learning algorithms could effectively solve complex nonlinear problems and predict better than traditional prediction methods (Weron, 2014; Yu et al., 2015; Márquez-Chamorro et al., 2015). As an important branch in the field of machine learning, the task of time series prediction was explored in depth. Due to the availability of large amounts of historical data and the need for accurate prediction of future data, more and more machine learning strategies were being developed and used for time series prediction tasks (Wang et al., 2022).

For instance, Abbasimehr et al., (2020) used Long Short-Term Memory networks (LSTM) neural network algorithm to identify highly fluctuating features in time series and effectively improve the business competitiveness of enterprises (Abbasimehr et al., 2020). Li et al., (2021) analyzed the differences in building energy consumption in different climate zones and realized short-term energy consumption prediction (Li et al., 2021). Ghimire et al., (2024) extracted features of actual electricity demand data through a machine learning algorithm to realize an accurate prediction of electricity demand for energy industry operations, which provides an auxiliary decision-making tool for the development of the energy industry (Ghimire et al., 2024).

Building energy usage data could be used for building energy consumption time series prediction tasks to optimize energy management (Abrishambaf et al., 2018; Kim and Cho, 2019; Zhuang et al., 2023). Hospital outpatient building power consumption data was collected infrequently, often on a monthly basis. With the rapid socio-economic development, the total energy consumption of various industries was increasing year by year (Khalil et al., 2024; Zhu et al., 2022). Electricity usage data in hospital buildings was highly time-dependent (Gordillo-Orquera et al., 2018). The reference value of early data was extremely low. As a result, valid data on electricity consumption in hospital outpatient buildings mostly belong to small data volume samples. Most of the machine learning based prediction task methods were difficult to extract the data features in small data volume samples, and the credibility of the prediction results was low (Lin et al., 2023). Therefore, there was an urgent need for a short-term time series forecasting algorithm that was stable, has high forecasting accuracy and was suitable for small data volume samples (Chang et al., 2016; Wu et al., 2019).

Neural networks were good at recognizing nonlinear features in time series, but there were risks of stochasticity and overfitting with smaller amounts of data (Cheng et al., 2023; Zhang et al., 2022). Some more stable and structurally simple algorithms were more suitable for the task of predicting electricity consumption in outpatient buildings. Due to the introduction of insensitive spaces ϵ , Support Vector Regression (SVR) algorithms were gradually becoming the method for time series forecasting tasks with nonlinear characteristics (Wu et al., 2023; Liu and Dai, 2023). SVR algorithm was suitable for identifying data features from small data volume samples (Zhang et al., 2018). The high prediction accuracy of the SVR algorithm in the electricity consumption prediction task was also demonstrated (Taghavifar and Mardani, 2014; Che et al., 2012; Hu et al., 2015; Taghavifar et al., 2015; Zapiain et al., 2022). However, the SVR algorithm was mainly affected by three hyperparameters, the penalty coefficient C , the kernel function parameter γ and the insensitive space ϵ . Improper selection of hyperparameter values could lead to overfitting or underfitting of the algorithm. Therefore, the key to improve the prediction accuracy of the SVR algorithm lies in obtaining the global optimal solutions of the three hyperparameters (Peng et al., 2023). However, there was still no generalized guideline on how to choose the globally optimal solution for the three hyperparameters (Schölkopf et al., 1997). On this basis, introducing an optimization algorithm to find the global optimal solution of the hyperparameters was a feasible solution.

Hu et al. developed a Particle Swarm Optimization-Support Vector Regression (PSO-SVR) model in their study on syrup brix prediction, using Particle Swarm Optimization to optimize the penalty coefficient and kernel parameters of Support Vector Regression, and demonstrated its excellent predictive performance (Hu et al., 2023). Jaafari et al. introduced the Grey Wolf Optimizer-Support Vector Regression (GWO-SVR) model in their study on identifying high-growth areas for poplar cultivation. Compared to the PSO-SVR model and the standalone SVR model, the GWO-SVR model demonstrated superior predictive performance (Jaafari, 2023). Javed et al. introduced the Firefly Optimization Algorithm-Support Vector Regression (FOA-SVR) model in their study on predicting the compressive strength of steel fiber-reinforced concrete. Compared to the PSO-SVR and GWO-SVR models, the FOA-SVR model demonstrated superior predictive performance on a small-sample dataset of 304 instances, suggesting that it may offer certain advantages under limited data conditions (Javed et al., 2024). However, in Javed's study, only two hyperparameters of the SVR model were optimized. Expanding the number of optimized hyperparameters could potentially enable a more precise search for the global optimum.

In this work, a novel FOA-SVR hybrid strategy was proposed by integrating the Firefly Optimization Algorithm (FOA) with the Support Vector Regression (SVR) model to optimize its three key hyperparameters. This strategy leverages the global search capability of FOA to enhance the predictive performance of SVR. The effectiveness of the proposed hybrid model was validated using real-world electricity consumption data from hospital outpatient buildings under limited data conditions. The study compared the effects of different optimization algorithms on the predictive accuracy of SVR, examined the impact of data length on prediction performance, and further demonstrated the adaptability of SVR by comparing the optimized model against other commonly used

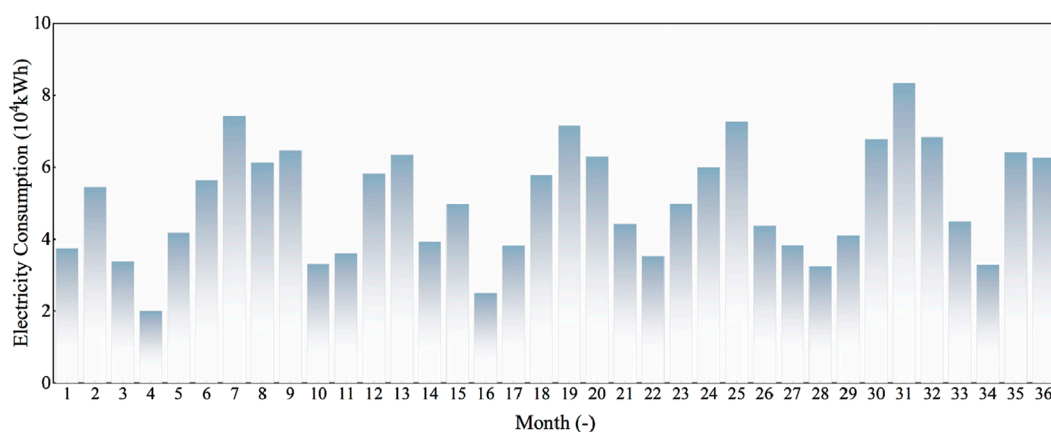


FIGURE 1
Three years of electricity consumption data for hospital outpatient building.

algorithms. These results collectively confirm the applicability and effectiveness of the proposed FOA-SVR strategy in small-sample scenarios.

The rest of the paper was organized as follows. In [Section 2](#), describes data sources and preprocessing, SVR algorithm, SVR algorithm optimized by FOA. In [Section 3](#), the effects of firefly population sizes and data lengths on prediction accuracy were compared. Meanwhile, the excellence of the FOA-SVR hybrid strategy was verified by different optimization algorithms and traditional algorithms. In [Section 4](#), the conclusion was given.

2 Materials and methods

2.1 Data acquisition and data pre-processing

In this work, a typical hospital in China was taken as an example. By investigating the energy consumption data of the outpatient building in hospital for a cumulative period of 3 years, the month-by-month electricity consumption of the outpatient building in hospital was obtained. Although the dataset used is relatively limited in size, it reflects the common constraints in data availability within hospital energy systems. The aim of this work is to develop predictive modeling strategies that remain effective under such limited data conditions, which are frequently encountered in real-world medical settings. The major energy-consuming equipment in the outpatient building includes ventilators, fully automated biochemistry analyzers, modular biochemistry and immunoassay systems, centrifuges, and water treatment units. The cumulative 3-year electricity consumption of the outpatient building in hospital was shown in [Figure 1](#).

By analysis of data, the monthly power consumption of the outpatient building of the hospital was more than 1×10^4 kWh. The order of magnitude of electricity consumption was at 10^4 , and the range of data characteristics varies widely. Differences in the magnitude of the gradients of different features lead to inconsistent convergence speeds of the algorithm, or even to local optimal

solutions. The normalization of the data makes the values of each feature in the same magnitude, and the optimization process was more stable and converges faster. Through data normalization, it was ensured that all features were within the same numerical range to avoid the serious impact on the hybrid strategy prediction accuracy caused by the large numerical range of some features. In this work, the data normalization algorithm was selected to preprocess the electricity consumption data. The normalized data range was $[-1, 1]$. Finally, the prediction results were inverse normalized to obtain the predicted electricity consumption of the corresponding order of magnitude. Data normalization and inverse normalization were calculated by [Equations 1, 2](#), respectively.

$$x_{\text{nor}} = 2 \times \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

$$x_{\text{ori}} = 0.5 \times (x_{\text{nor}} + 1) \times (\max(x) - \min(x)) + \min(x) \quad (2)$$

where x was the electricity consumption of the hospital outpatient building, x_{nor} was the normalized electricity consumption with the value range of $[-1, 1]$, and x_{ori} was the electricity consumption after inverse normalization.

All experiments in this study were carried out on a laptop with an AMD R-7945HX processor and an 8 GB RTX4060 GPU. This hardware setup offers a good balance between computational efficiency and practical feasibility, supporting potential integration into real-world hospital operations.

2.2 Predictive principles of SVR algorithm

SVR was a regression method based on the principle of support vector machine, which was widely used to deal with nonlinear regression and prediction problems. By introducing the kernel function parameter γ (usually associated with kernel functions such as Gaussian kernel, polynomial kernel, etc.), the data was mapped by the SVR algorithm from a low-dimensional space to a high-dimensional feature space. In higher dimensional spaces, linear regression algorithms could be used to fit complex nonlinear

relationships. The complexity of the SVR algorithm was controlled by the penalty coefficient C . By varying the range of C , the data fitting ability was balanced with the generalization ability and overfitting of the SVR algorithm was avoided. In addition, the SVR has the width ε of the error-insensitive region. By allowing a range of prediction errors to be ignored, the robustness of the SVR algorithm to noise was enhanced. The SVR algorithm has some advantages when dealing with small data sets. However, the computational complexity and computational cost of SVR increase significantly when the dataset size was large. In addition, SVR was limited by support vectors and was ineffective on large-scale datasets. SVR algorithm prediction accuracy was affected by hyperparameter values. The key hyperparameters of the SVR algorithm include the penalty coefficient C , the insensitive region ε , and the kernel function parameter γ . There were differences in the effects of different hyperparameters on the prediction accuracy of the SVR algorithm. There were interactions between different hyperparameters. The prediction accuracy of SVR algorithms could be improved by reasonable values of hyperparameters. The principle of the SVR algorithm was described by Equation 3

$$\hat{y} = \sum_{i=1}^m (\alpha_i - \alpha_i^*) K(z_i, x) + b = \sum_{i=1}^m (\alpha_i - \alpha_i^*) \exp(-\gamma \|z_i - x\|^2) + b \quad (3)$$

where $\hat{y}$ was the predicted value, m was the number of support vectors, α_i and α_i^* were Lagrange multipliers, $K(z_i, x)$ was the Gaussian kernel function, z_i was the support vectors, b was the bias term, and γ was the kernel function parameter, which was used to control the width of the Gaussian kernel.

2.3 Predictive principles of the FOA-SVR hybrid strategy

The amount of data on electricity consumption in hospital outpatient buildings was small, and the ability of the prediction hybrid strategy to extract data features directly determines the prediction accuracy. The key hyperparameters that affect the feature extraction capability of the SVR algorithm were the penalty coefficient C , the kernel function parameter γ and the insensitivity zone ε . In this work, a FOA-SVR hybrid strategy was proposed where the hyperparameter values of the SVR algorithm were optimized by the FOA to improve the prediction accuracy for small data volume samples. The prediction accuracy of the established FOA-SVR hybrid strategy was influenced by the number and type of optimization hyperparameters on. The three hyperparameters were co-optimized and the local optimal solution probability was reduced.

FOA was an intelligent optimization algorithm based on the luminous behavior of fireflies in nature. The optimal solution of the FOA was obtained by modeling mutual attraction and random motion search between fireflies. Fireflies were attractive to other individuals and the attraction was proportional to the intensity of their luminescence and inversely proportional to distance. The brightness of a firefly was related to the value of its objective function. A group of fireflies was randomly initialized, with each firefly representing a possible solution, and the dimensions of the initial solutions were the same as the number of hyperparameters

to be optimized. The brightness of each firefly was calculated (brightness was inversely proportional to the value of the objective function). During the hyperparameter optimization, the difference in brightness of each firefly from the other fireflies was calculated. If a brighter firefly was present, the current firefly was attracted and moves toward the new firefly. Each individual of FOA represents a set of hyperparameter combinations. The position of the firefly was continuously updated in FOA and the hybrid strategy performance was incrementally improved. Eventually, the hyperparameter combination corresponding to the brightest firefly was selected as the optimal solution. The principle of the FOA-SVR hybrid strategy for predicting electricity consumption in outpatient buildings was shown in Figure 2.

In the FOA-SVR hybrid strategy, the penalty coefficient C , the kernel function parameter γ , and the insensitivity zone ε were co-optimized. The optimization objective was set to minimize the root mean square error of the SVR algorithm. These three hyperparameters are set as the vector P_i as shown Equation 4

$$P_i = [C_i, \gamma_i, \varepsilon_i] \quad (4)$$

The adaptational degree of the candidate solution P_i was calculated by Equation 5

$$RMSE_i = \sqrt{\frac{1}{n} \sum_{j=1}^n (\hat{y}_i(P_i) - \hat{y}_j)} \quad (5)$$

The attractiveness of fireflies β_{ij} was calculated using Equation 6

$$\beta_{ij} = \beta_0 \exp(-\theta r_{ij}^2) \quad (6)$$

where β_0 is the initial attraction, θ was the attraction decay coefficient, and r_{ij} was the Euclidean distance between fireflies i and j .

If the adaptation of firefly i was lower than that of firefly j , firefly i was attracted and moves. The position of the firefly during its movement is calculated by Equation 7

$$P_i^* = P_i + \beta_{ij} + (P_i + P_j) + \delta(\text{rand}(1, \text{dim}) - 0.5) \quad (7)$$

where P_i^* is the position of firefly i after updating, δ was the dynamic step factor, and $(\text{rand}(1, \text{dim}) - 0.5)$ was the random perturbation term. When the adaptation was minimized, the values of the three hyperparameters C , ε , and γ corresponding to P_i were the corresponding globally optimal solutions.

3 Results and discussions

3.1 Electricity consumption projection for outpatient building

The number of individuals involved in the search in each generation in FOA was determined by the number of individual fireflies. The higher the number, the more random the initial position of the fireflies, the search space was enlarged, which could better avoid the local optimum. The computational and time complexity of the FOA-SVR hybrid strategy increases accordingly. The predictive performance indicator s of the FOA-SVR hybrid strategy for the

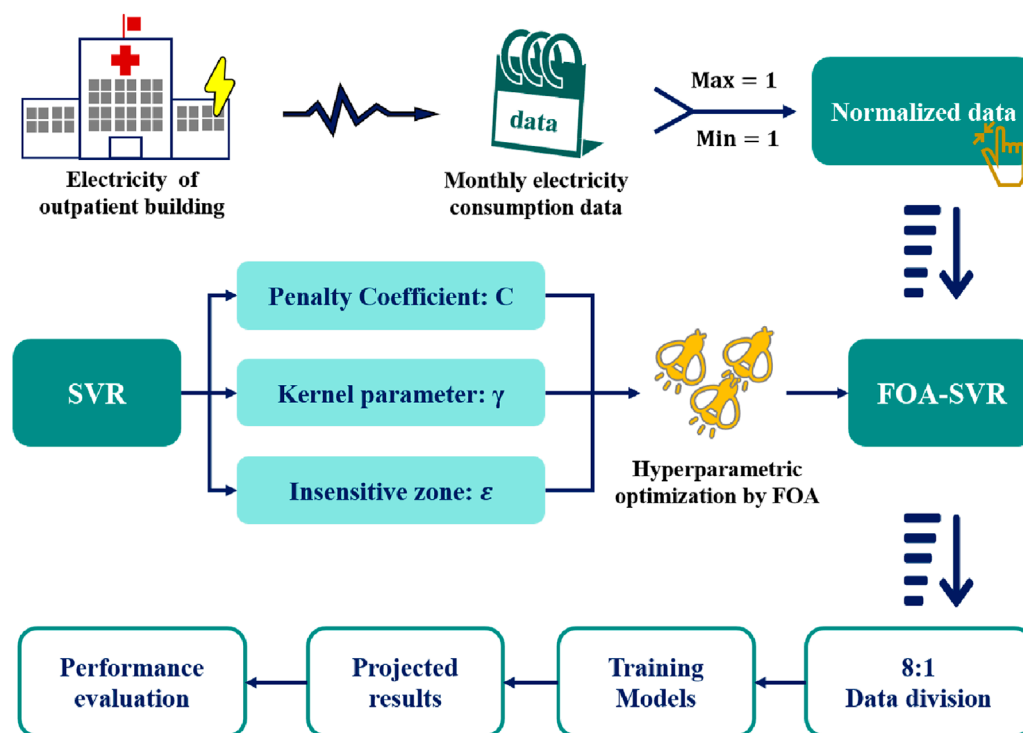


FIGURE 2
Schematic diagram of FOA-SVR hybrid strategy for electricity consumption prediction.

electricity consumption of the outpatient building when the number of fireflies was 0, 5, 15, 20, 25, 30, 35, and 40 were shown in Table 1. It was worth noting that the process of optimization algorithm for finding the globally optimal solution was stochastic in nature. The idea of integrated learning was introduced in the FOA-SVR hybrid strategy. For each firefly population algorithm, each was predicted ten times and the results were averaged to reduce the error of randomness on the performance of the FOA-SVR hybrid strategy. A firefly count of 0 represents an unoptimized SVR algorithm. To comprehensively evaluate model performance, a set of complementary metrics was adopted. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) were used to assess the magnitude of prediction errors from both absolute and relative perspectives. In parallel, the Coefficient of Determination (R^2) and Pearson Correlation Coefficient (PCC) were employed to quantify the correlation and trend similarity between the predicted and actual values. Among them, R^2 was selected as the primary evaluation metric in this study, as it emphasizes the agreement of temporal variation patterns, which is particularly important in short-term energy forecasting scenarios. Together, these metrics provide a balanced assessment of both the accuracy of numerical predictions and the consistency of variation patterns. The PCC values under the eight conditions were all above 0.9, indicating that the FOA-SVR hybrid strategy has a good ability to characterize the variation of electricity consumption data in hospital outpatient buildings with a small sample data size. The prediction accuracy of the FOA-SVR hybrid strategy was much lower for firefly counts of 0 and 5 than for the other six cases. The number of fireflies was too

small and the available optimization range of SVR hyperparameters was insufficient. The hyperparameter optimization result deviates from the global optimal solution by a large margin and negative optimization occurs. In addition, the prediction accuracy gradually increased with the increase in firefly population size. The R^2 is highlighted as a representative measure of the alignment between predicted and actual trends, given its interpretability in assessing directional consistency. This emphasis is complementary to the error-based indicators, which are used throughout the study to provide a balanced evaluation of predictive accuracy. Taking R^2 as an example, this indicator was 0.764 and 0.804 for firefly counts of 10 and 15, respectively. The R^2 of the single SVR algorithm was only 0.687, therefore, the prediction accuracy of the SVR algorithm was significantly improved by the FOA. The R^2 was 0.818, 0.835, and 0.855 for firefly counts of 20, 25, 30, and 35, respectively. Within this range, the prediction accuracy of the FOA-SVR hybrid strategy increased synchronously with the number of fireflies. The FOA-SVR hybrid strategy has high accuracy in predicting electricity consumption data for hospital outpatient buildings. The prediction accuracy of the FOA-SVR hybrid strategy increased with the number of fireflies and stabilized at a population size of 30. When the firefly population was 35 and 40, the predictive accuracy indicator R^2 of electricity consumption in the outpatient building was around 0.855. At this time, the effect of firefly population increments on FOA-SVR hybrid strategy predictions was weak. The prediction time of the FOA-SVR hybrid strategy increased dramatically as firefly populations increased. Therefore, the FOA-SVR hybrid strategy has the advantage of both prediction accuracy and computation time for predicting the electricity consumption of hospital outpatient

TABLE 1 Prediction accuracy of the FOA-SVR hybrid strategy under different firefly population sizes.

Population size	MAPE	RMSE	PCC	MAE	MSE	R ²
0 Firefly	50.19433	0.226219	0.931515	0.197669	0.051175	0.694899
5 Firefly	58.39602	0.226384	0.874546	0.196776	0.052565	0.686614
10 Firefly	46.91373	0.195058	0.888519	0.171743	0.040541	0.758296
15 Firefly	43.2594	0.1798	0.919565	0.15916	0.032813	0.804371
20 Firefly	41.00853	0.173804	0.915341	0.153341	0.030594	0.817603
25 Firefly	37.63501	0.165552	0.921539	0.145855	0.027634	0.835247
30 Firefly	36.85142	0.155862	0.931139	0.142602	0.024354	0.854803
35 Firefly	35.17414	0.15579	0.935207	0.138282	0.024343	0.854872
40 Firefly	38.16317	0.161734	0.927174	0.144768	0.026225	0.84365

buildings with small data volume when the firefly population size was 30.

The results, prediction accuracy indicators, and hyperparameters of the ten predictions of the FOA-SVR hybrid strategy at a firefly population size of 30 were shown in Table 2, Tables 3, 4. In these tables, the FOA was more effective for hyperparameter optimization of SVR algorithm. The prediction accuracy of the optimized hybrid strategy was higher and the prediction results were stable. However, the hyperparameters obtained by the optimization algorithm were not always optimal solutions. In the 9th iteration prediction, the penalty coefficient C and kernel function parameter γ obtained by FOA show outliers, which were significantly different from the other 9 optimization results. Due to the anomalies in the penalty coefficient C and the kernel function parameter γ , the 9th prediction slips significantly in value. This highlights the necessity of repeated experiments, as single-run results may be skewed by the inherent randomness of metaheuristic optimization. Performing multiple independent runs allows for a more reliable evaluation of model performance and helps mitigate the influence of outlier parameter combinations. The predicted resultant consumptions of the FOA-SVR hybrid strategy for the electricity consumption of the outpatient building were 39,394.39 kWh, 38,840.88 kWh, 53,964.86 kWh, and 59,744.73 kWh, respectively. The predictive accuracy indicators of the FOA-SVR hybrid strategy also indicate the lack of accuracy of the predictive results. In particular, the coefficient of determination R^2 slipped to 0.82. This error reduces the prediction accuracy of the FOA-SVR hybrid strategy when the number of fireflies was 30. Therefore, it was reasonable and necessary to exclude the effect of stochasticity in the FOA-SVR hybrid strategy through integrated learning of multiple predictions. To verify the model's robustness under limited data conditions, ten independent runs were conducted using randomized training/testing splits at a ratio of 8:1. The prediction performance was assessed using MAE and RMSE, and the results were reported as mean $\pm$ standard deviation. The model achieved MAE = 4516.05 ± 489.44 and RMSE = 4936.01 ± 260.84 , indicating stable and consistent performance across different data partitions.

Figure 3 demonstrates the difference between the predicted results of the FOA-SVR hybrid strategy for the electricity consumption of the hospital outpatient building and the predicted results of the single SVR algorithm with respect to the true value when the number of fireflies was 30 and the maximum number of iterations was 20. The FOA-SVR hybrid strategy data trend change fitting performance was good. Based on the SVR algorithm, the prediction results of the FOA-SVR hybrid strategy were closer to the real values, and the prediction accuracy was significantly improved. In addition, it could be seen from the error bars of the prediction results of the FOA-SVR hybrid strategy that the prediction results of the FOA-SVR hybrid strategy were more stable without large fluctuations and were generalizable. It was worth noting that although the prediction accuracy of the FOA-SVR hybrid strategy was higher than the prediction accuracy of the single SVR algorithm, there were still some differences from the true values in the numerical values of the prediction results. The difficulty of extracting data features was increased by a smaller sample size of data. The FOA-SVR hybrid strategy has strong data feature extraction capability, but was still limited by too small a data sample size.

3.2 Effect of optimization algorithms on the SVR prediction accuracy

When the population size was 30, the prediction accuracy indicators of three different algorithms, Sparrow Search Algorithm (SSA), Seagull Optimization Algorithm (SOA) and FOA, after optimizing the hyper-parameters of the SVR algorithm were shown in Table 5. All three optimization algorithms optimize the penalty coefficient C , the kernel function parameter γ , and the insensitivity band ϵ of the SVR algorithm. The SVR algorithm predicts results without randomness and does not require integrated learning. To ensure the feasibility of a side-by-side comparison with the FOA-SVR hybrid strategy, the SOA-SVR algorithm, and the SSA-SVR hybrid strategy runtimes, the SVR algorithm runtimes were scaled up by a factor of ten. The single SVR algorithm has a

TABLE 2 Ten prediction results from the FOA-SVR hybrid strategy.

Prediction round	33rd month	34th month	35th month	36th month
1st	44,108.4	38,182.65	57,336.46	66,482.95
2nd	43,264.15	38,535.58	57,769.56	66,912.61
3rd	43,206.03	39,136.52	58,607.93	67,202.95
4th	43,256.84	39,943.37	58,158.02	64,413.3
5th	41,030.6	37,297.49	56,370.96	66,757.9
6th	43,599.88	39,335.77	58,156.26	65,908.17
7th	43,882.84	39,512.61	57,297.28	63,374.49
8th	42,841.18	39,229.16	58,065.46	65,714.44
9th	39,271.84	38,870.93	58,554.57	67,407.22
10th	41,802.3	39,522.16	59,001.35	66,843.59

TABLE 3 Accuracy indicators of the ten predictions of the FOA-SVR hybrid strategy.

Prediction round	MAPE	RMSE	PCC	MAE	MSE	R ²
1st	32.45844	0.150091	0.9345	0.132501	0.022527	0.865694
2nd	36.14044	0.153155	0.930072	0.141925	0.023457	0.860154
3rd	36.1347	0.153186	0.931845	0.142801	0.023466	0.860098
4th	31.51891	0.151294	0.943366	0.130299	0.02289	0.863533
5th	45.14185	0.167151	0.914684	0.159603	0.027939	0.833428
6th	32.8892	0.1501	0.938184	0.13461	0.02253	0.865677
7th	27.99432	0.151878	0.950844	0.120551	0.023067	0.862477
8th	35.26795	0.150886	0.935329	0.138945	0.022767	0.864267
9th	50.788	0.174305	0.906134	0.173796	0.030382	0.818865
10th	40.18041	0.156578	0.92643	0.150984	0.024517	0.853833

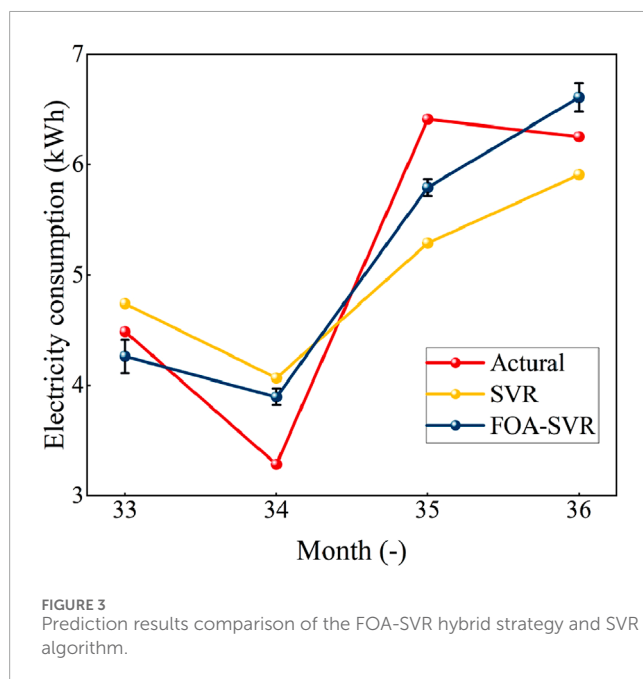
simple structure and has a much higher run rate than the superior SSA-SVR, SOA-SVR, and the FOA-SVR hybrid strategy, with only 9.550 s required for ten runs. The SOA-SVR hybrid strategy has high prediction accuracy with seven prediction accuracy indicators of 36.851, 0.156, 0.931, 0.143, 0.024, and 0.855 for MAPE, RMSE, PCC, MAE, MSE, and R², respectively, but the runtime was longer with a total of 50.577 s. The SOA-SVR hybrid strategy has a high prediction accuracy of 36.851, 0.156, 0.931, 0.143, 0.024, and 0.855, respectively. The prediction accuracy of the FOA-SVR hybrid strategy was slightly improved from that of the SOA-SVR algorithm, with the seven indicators being 36.851, 0.156, 0.931, 0.143, 0.024, and 0.855, respectively. The total duration of the FOA-SVR hybrid strategy run was reduced to 29.365 s. The FOA-SVR hybrid strategy has higher accuracy as well as lower computational cost. It was worth noting that the SSA-SVR hybrid strategy computes a total time of 43.997 s, which was time-consuming, but the prediction accuracy was rather

inferior to that of the single SVR algorithm. Randomness and updating strategies may have caused the SSA-SVR hybrid strategy search direction to deviate from the globally optimal solution, and errors were thus generated. Therefore, the FOA-SVR hybrid strategy was more suitable for predicting electricity consumption in hospital outpatient buildings with small data sample size.

The difficulty of the hybrid strategy in extracting features from the data was determined by the length of the data. The more data features the hybrid strategy extracts, the more accurate the prediction results are. For the electricity consumption of hospital outpatient buildings, their energy consumption data collection was usually calculated on a monthly basis with a small sample size of data. This work collects energy consumption data for 3 years totaling 36 months. The number of samples collected fluctuates up and down within reasonable limits depending on demand. Therefore, validating the generalizability of the FOA-SVR hybrid strategy over

TABLE 4 Hyperparameters for ten predictions of the FOA-SVR hybrid strategy.

Prediction round	C	γ	ε
1st	4.241434	0.582067	0.107948
2nd	5.67813	0.556514	0.103036
3rd	5.524868	0.54574	0.096138
4th	3.858943	0.688794	0.087348
5th	8.06834	0.516039	0.114219
6th	4.169121	0.621413	0.094561
7th	3.010256	0.744377	0.094248
8th	5.758163	0.589669	0.095398
9th	11.25808	0.453056	0.095019
10th	7.747713	0.514232	0.090986



different data lengths was a must. Fluctuations in building energy consumption were characterized by seasonality. Seasonality was assumed to be largely characterized over a 3-year data volume. Random perturbations were added to the 36 raw data to generate electricity consumption data for the outpatient building with the same trend but different values. This was repeated twice to obtain electricity consumption data for the outpatient building for a total of 9 years totaling 108 months. Data sets of different data lengths were obtained using 18 months as the basic interval. In particular, 36 raw data were also clipped to explore the effect of smaller data samples on prediction accuracy. Again, the data were clipped at 18-month intervals to obtain the first 18 data of the original data as a control

group with a much smaller sample data size. The trend images for data lengths of 18, 36, 54, 72, 90, and 108 were shown in Figure 4.

The difference between the predicted and true values for the six data lengths was shown in Figure 5. To ensure the conditional consistency of the comparison process, the ratio of the training set to the test set remained 8:1. Figures 5a–f shows the difference between the predicted and true values of the four algorithms for data lengths of 18, 36, 54, 72, 90, and 108, respectively. As shown in Figure 5, the prediction accuracy generally improved with longer data sequences. Notably, the model trained on 36-month data did not produce the best results, suggesting that no overfitting occurred at this data length. These consistent trends across different configurations provide supporting evidence for the statistical reliability of the results. However, when the data length was 18, the SVR algorithm fails to extract the data features at all and the prediction accuracy indicator R^2 was -3.727 . The FOA-SVR, SOA-SVR and SSA-SVR algorithms lost a large number of data features. The prediction accuracy indicators R^2 of the three combined algorithms were 0.282, 0.282 and 0.270, respectively. The FOA-SVR and SOA-SVR algorithms have higher prediction accuracy when the data length was 36. The prediction accuracy indicators R^2 of both combined algorithms exceeds 0.83. The SSA-SVR and SVR algorithms had similar predictive effects but lower predictive accuracy, with none of the predictive accuracy indicator R^2 size exceeding 0.7. All three optimized SVR algorithms accurately identified the data features when the data length was greater than 72. The prediction accuracy indicator R^2 of the prediction results of the three combined algorithms exceeded 0.96. It was worth noting that in this work, the FOA-SVR hybrid strategy generalizes better than the other two optimization algorithms, and the prediction accuracy indicator, R^2 , was stable above 0.99. The prediction accuracy indicator R^2 also improves to near 0.9 when the training set data of the single SVR algorithm was greater than 72, which was a higher prediction accuracy, but not as good as the optimized SVR algorithm. Therefore, the FOA-SVR hybrid strategy was more suitable for the prediction of electricity consumption in hospital outpatient buildings with small sample data size compared to other combined algorithms and single SVR algorithm.

3.3 Effect of single algorithms on electricity consumption forecasting results

The differences between the predicted results and the true values of the FOA-SVR hybrid strategy and the five single prediction algorithms were shown in Figure 6. The five single algorithms were SVR, K-Nearest Neighbors (KNN), Autoregressive Integrated Moving Average (ARIMA), Decision Tree (DT) and Random Forest (RF). In this figure, the original data samples were small, and the KNN, ARIMA and RF algorithms were difficult to recognize the characteristics of data changes, and the prediction effect was poor. The VR algorithm and the DT algorithm were better predictors and fit the data of the test set better. However, these two algorithms were still inferior to the FOA-SVR hybrid strategy.

The seven prediction accuracy evaluation indicators for the FOA-SVR hybrid prediction strategy and five single prediction algorithms were shown in Table 6. The coefficient of determination R^2 of both SVR algorithm and DT algorithm was around 0.7 with

TABLE 5 Predictive performance of SVR algorithm under different optimization algorithms.

Algorithms	MAPE	RMSE	PCC	MAE	MSE	R ²	Time
FOA-SVR	36.851	0.156	0.931	0.143	0.024	0.855	29.365 s
SOA-SVR	34.004	0.157	0.939	0.137	0.025	0.851	50.557 s
SSA-SVR	63.796	0.237	0.853	0.216	0.056	0.665	43.997 s
SVR	50.194	0.226	0.932	0.198	0.051	0.695	0.955 s

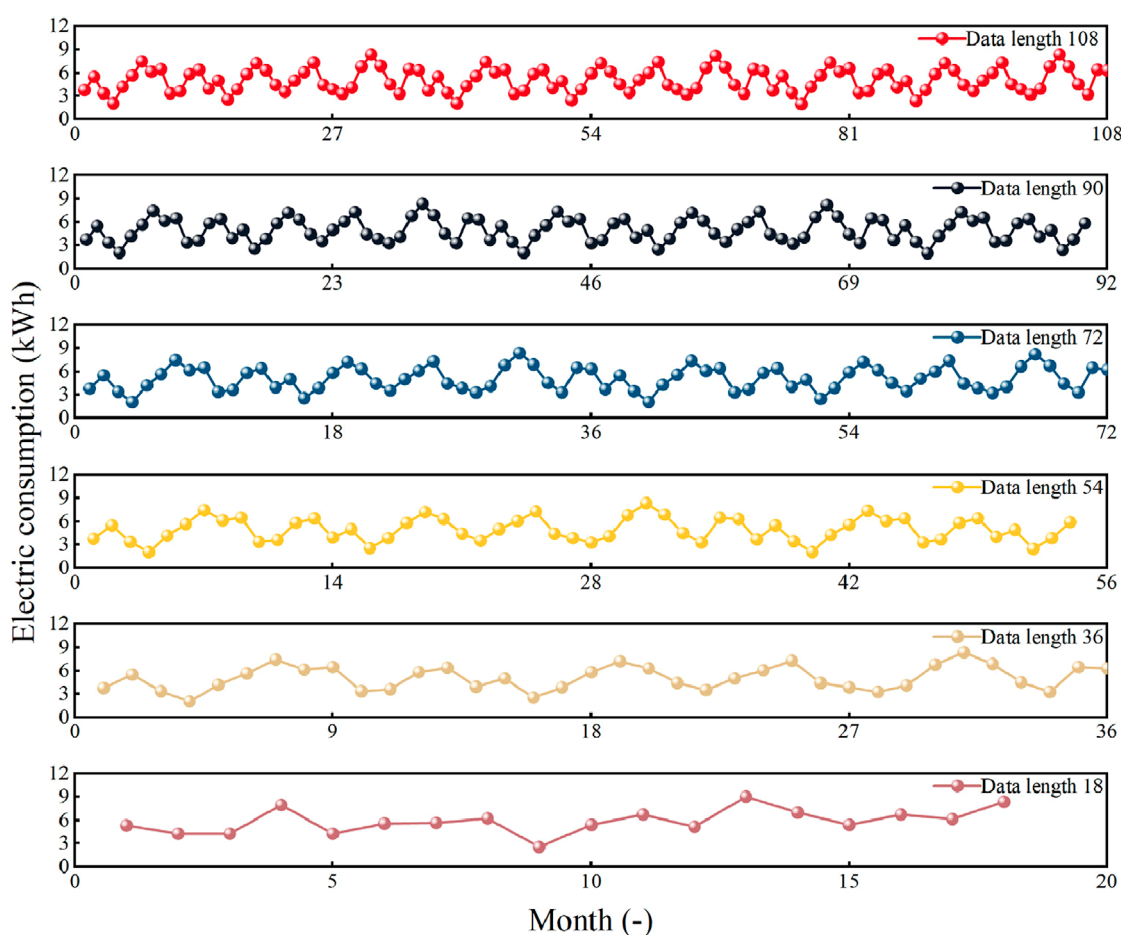


FIGURE 4
Different lengths of generated data based on electricity consumption characteristics of outpatient buildings.

high prediction accuracy. The anomaly of negative coefficient of determination R^2 for the KNN algorithm and ARIMA algorithm indicates that both prediction algorithms completely failed to identify the intrinsic correlation of the electricity consumption data of the hospital outpatient building. Under this condition, the KNN algorithm and ARIMA algorithm were not as effective as the simple mean algorithm in prediction. The RF algorithm has a coefficient of determination R^2 of 0.096, which was a weak explanation of the variables. The difference between its predicted and actual values of electricity consumption in the hospital outpatient building was explained by the predictive accuracy evaluation indicator R^2 for

five single algorithms. In particular, PCC serves as an important indicator of the linear correlation between predicted and actual values. The PCC value of the ARIMA algorithm was 0.85 with strong linear correlation, which was opposite to the results of the remaining several indicators for evaluating the prediction accuracy as well as the graphs of the predicted values. The sample data volume of electricity consumption in hospital outpatient buildings was small, but the characteristic relationship between the data was not a single linear relationship. Therefore, a single PCC value does not indicate the superiority of the predictive algorithm. The PCC must be combined with several remaining indicators for evaluating

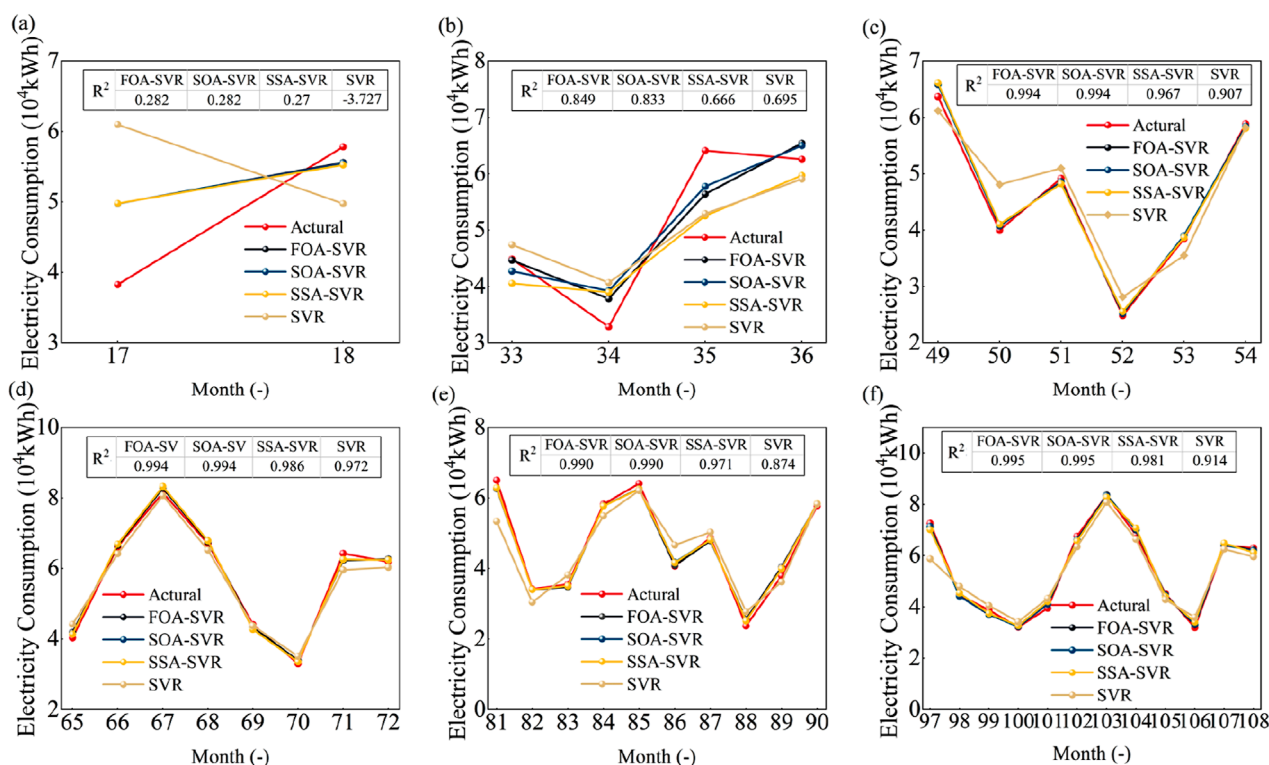


FIGURE 5

Results of electricity consumption forecasts with different data lengths. (a) 18 months, (b) 36 months, (c) 54 months, (d) 72 months, (e) 90 months, and (f) 108 months.

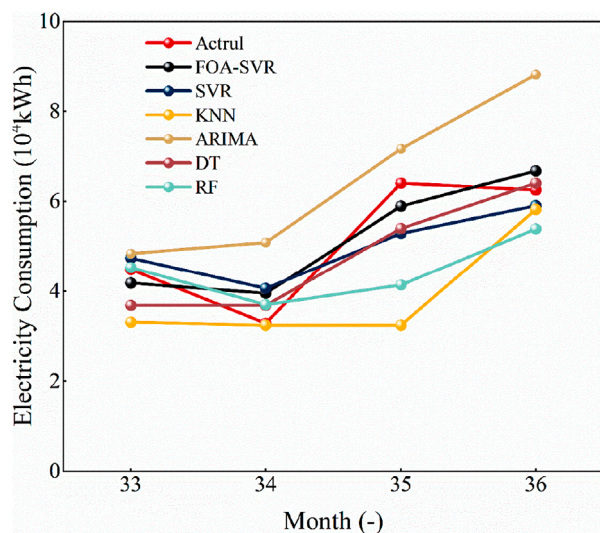


FIGURE 6

Differences in prediction results between the FOA-SVR hybrid strategy and five single algorithms.

prediction accuracy to make a comprehensive judgment. The SVR algorithm has a prediction accuracy indicator PCC of 0.93, which was greater than 0.89 of the DT algorithms, but the prediction of SVR algorithm is, on the contrary, slightly less effective than the

DT algorithm. Overall, the ability demand of the hybrid strategy to extract data features was high in the prediction of electricity consumption in hospital outpatient buildings with a small sample size of data. In particular, prediction algorithms with stochastic nature were difficult to apply to the prediction process with small sample size of data. The SVR algorithm, with its strong data feature extraction capability and high prediction accuracy, was suitable for the process of predicting electricity consumption in hospital outpatient buildings. The prediction accuracy of SVR algorithms could be further improved by optimization algorithms.

The prediction accuracy indicators of several commonly used neural network algorithms Radial Basis Function (RBF) neural network, Backpropagation (BP) neural network, Elman (ELMAN) neural network and LSTM neural network were shown in Table 7. For neural network algorithms, it was common to have algorithms characterized by high complexity and stochasticity. The higher complexity of neural network algorithms and the presence of randomness could lead to some important data features being ignored when the hybrid strategy learns the data features, which could seriously affect the prediction accuracy. The four algorithms, RBF, BP, ELMAN and LSTM algorithms, have a prediction accuracy evaluation indicator R^2 of -3.278 , -1.402 , -0.055 and -0.387 , respectively, which were all less than zero. The results show that the four neural network algorithms have a prediction result error even larger than the error between the mean of the training set and the test set of the original data during the prediction of energy consumption of healthcare buildings with a small sample size of data. Therefore, it was necessary to choose a simple

TABLE 6 Differences in predictive performance between the FOA-SVR hybrid strategy and five single algorithms.

Algorithms	MAPE	RMSE	PCC	MAE	MSE	R ²
FOA-SVR	36.85142	0.155862	0.931139	0.142602	0.024354	0.854803
SVR	50.19433	0.226219	0.931515	0.197669	0.051175	0.694899
K-NN	117.2943	0.537727	0.507633	0.380285	0.28915	−0.72389
ARIMA	111.0664	0.511842	0.847215	0.432404	0.261983	−0.56192
DT	58.65319	0.214588	0.886107	0.186706	0.046048	0.725467
RF	72.37495	0.389401	0.617675	0.283107	0.151633	0.095977

TABLE 7 Neural network predicts outpatient building electricity usage data.

Algorithms	MAPE	RMSE	PCC	MAE	MSE	R ²
RBF	274.619	0.847	0.512	0.644	0.718	−3.278
BP	151.951	0.635	0.532	0.497	0.403	−1.402
ELMAN	84.604	0.421	0.797	0.317	0.177	−0.055
LSTM	95.599	0.482	0.517	0.372	0.233	−0.387

but strong data feature recognition capability such as SVR algorithm in the prediction process of small sample dataset. In contrast, the optimization algorithm does not increase the complexity of the SVR algorithm and optimizes the selection of hyperparameters of the SVR algorithm only based on the data characteristics. Optimization of SVR algorithm using optimization algorithm was a feasible solution for predicting electricity consumption in hospital outpatient buildings.

4 Conclusion

This work explores the effectiveness of an SVR prediction algorithm optimized with hyperparameters by the FOA in terms of predicting electricity consumption of outpatient buildings in hospital. The search space was enlarged by increasing the number of firefly populations to improve the possibility of finding a globally optimal solution. At the same time, the effect of randomness of the optimization algorithm was reduced by ensemble learning to improve the prediction accuracy of the algorithm. The specific conclusions were as follows.

1. The performance of the FOA-SVR hybrid strategy tends to stabilize as the firefly population size increases, with a slight increase in accuracy and a significant decrease in computational performance when the population size exceeds 30. The optimal number of fireflies during the prediction of electricity consumption in outpatient buildings with a small sample size of data was 30. The incremental computational cost does not provide a reasonable return on prediction accuracy after the population size was greater than 30.
2. The FOA-SVR hybrid strategy with a firefly population size of 30 achieves a balance between prediction accuracy and

computational efficiency, which was well suited for small-sample data scenarios such as the prediction of electricity consumption in hospital outpatient buildings. The FOA-SVR hybrid strategy consistently outperforms the single SVR algorithm and other optimization-based SVR algorithms (SSA-SVR, SOA-SVR) in terms of prediction accuracy and robustness under different data lengths. Data features were difficult to be extracted by the hybrid strategy when the data volume was lower than 36. The prediction accuracy of the FOA-SVR hybrid strategy rises significantly when the sample capacity was increased appropriately.

3. For the prediction process of electricity consumption in hospital outpatient building with small sample data volume, the complexity and stochasticity of the hybrid strategy increase the difficulty of data feature extraction, and the prediction accuracy decreases significantly. In a single algorithm, the SVR algorithm data feature extraction capability was strong. The FOA-SVR hybrid strategy optimized by the FOA improved the seven accuracy indicators to 36.85142, 0.156, 0.931, 0.143, 0.024, and 0.855, respectively, with the best results. When comparing different single prediction algorithms, it was evident that simple algorithms such as SVR optimized using FOA were more effective than complex neural network algorithms (RBF, BP, ELMAN, LSTM) in a small sample data environment. Neural network algorithms have difficulty in capturing the underlying data features, resulting in poorer predictions.

In conclusion, the FOA-SVR hybrid strategy demonstrates promising performance in predicting electricity consumption in hospital outpatient buildings under limited data conditions, as

evidenced by the empirical results presented in this study. The results show that combining SVR with optimization algorithms such as FOA was a feasible approach to improve the accuracy of the hybrid strategy without introducing unnecessary complexity, making it a practical choice for similar prediction tasks in small sample data environments.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

CL: Data curation, Investigation, Software, Writing – original draft, Writing – review and editing. GW: Data curation, Methodology, Project administration, Visualization, Writing – review and editing. LZ: Conceptualization, Investigation, Software, Writing – review and editing. QY: Data curation, Formal Analysis, Methodology, Project administration, Validation, Writing – review and editing. YY: Formal Analysis, Methodology, Project administration, Validation, Visualization, Writing – review and editing. QX: Formal Analysis, Funding acquisition, Project administration, Resources, Visualization, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Nomenclature

Variant

b	The bias term
C_i	The penalty coefficient
$K(z_i, x)$	The Gaussian kernel function
P_i	The position of firefly
P_i^*	The position of firefly i after updating
r_{ij}	The Euclidean distance between fireflies i and j
$x_{\text{normalized}}$	The normalized electricity consumption
x_{original}	The electricity consumption after inverse normalization
$\hat{y}$	The projected electricity consumption
z_i	The support vectors
α_i and α_i^*	The Lagrange multipliers
β_0	The initial attraction
β_{ij}	The updated attraction
γ_i	The kernel function parameter
ε_i	The insensitivity zone
θ	The attraction decay coefficient
δ	The dynamic step factor