Journal of Scientific & Industrial Research
Vol. 84, August 2025, pp. 871-878
DOI: 10.56042/jsir.v84i8.15204

The PSO-SVR-based Prediction Method for Electric Energy Substitution in Fishery

Qian Cao[1], Zhenyu Cui[1], Juan Su[1]*, Jingyi Lin[2], Fanpeng Bu[2] & Yi Lin[3]
[1]College of Information and Electrical Engineering, China Agricultural University, Beijing, China
[2]China Electric Power Research Institute Co. Ltd, Beijing, China
[3]State Grid Fujian Power Electric Co., Ltd, Fuzhou, China

Received 20 November 2024; revised 19 March 2025; accepted 12 June 2025

Following the proposal of "carbon neutrality and peak carbon emissions" goals, electrical energy substitution has emerged as a key strategy for sustainable development across various industries. As a crucial component of agricultural development globally, this paper introduces a particle swarm optimization vector regression method to predict the potential for electrical energy substitution in the fisheries sector. Initially, this article analyzes the key factors influencing the electrical energy substitution in fisheries from technological, economic, and policy perspectives. To explore how these various factors influence the potential for energy substitution, a Support Vector Regression (SVR) algorithm is applied. This SVR model's performance is subsequently improved by optimizing its parameters using Particle Swarm Optimization (PSO).Compared to a BP neural algorithm, the enhanced particle swarm optimization (PSO)-SVR model demonstrated markedly superior prediction accuracy and goodness-of-fit. Consequently, this model was effectively utilized to generate a forecast of the electrical energy substitution potential within China's fisheries in recent years. This study provides theoretical and data support for promoting electrical energy substitution in the fisheries sector and offers guidance for analyzing the potential for energy substitution.

Keywords: Carbon emission reduction, Energy transition, Particle swarm optimization, Potential prediction, Support vector regression

Introduction

Currently, the global energy transition is accelerating, and China has also accelerated its research efforts in the field of electrical energy substitution.[1] In the context of the national 'carbon neutrality and carbon peaking' objectives, the marine fishery sector holds a significant position in both the exploitation and sustainable development of ocean resources, while concurrently addressing the escalating demand for aquatic products.However, fisheries have long been dependent on traditional fossil fuels, and the high energy consumption and pollution caused by conventional fishing methods have seriously impacted both the atmospheric environment and marine ecosystems. Small-scale fisheries are gradually being replaced by large-scale industrial fisheries, and the application of electrical equipment in this process has become increasingly widespread and important.[2] Therefore, there is an urgent need to analyze the potential of electrical energy substitution for traditional energy sources to promote the green transition and sustainable development of fisheries.[3]

Currently, research on the substitution of electrical energy in agricultural production is mainly focused on its application in the context of carbon neutrality. Most studies emphasize the technical applications and advantages of electrical energy substitution in reducing agricultural carbon emissions, exploring the potential and application scenarios of solar and biomass energy. In 2023, Wu *et al.* examined how technologies related to electrical energy substitution could reduce agricultural carbon emissions and applied these technologies to modern fisheries, detailing their principles and advantages.[4] However, the article did not elaborate on the specific technical equipment involved in electrical energy substitution. Dai *et al.* developed a wind vector sensor that can respond sensitively to the environment without an external power source, meeting the needs of modern sustainable agricultural development.[5] As the global population and economy continue to grow, the interconnections between water, food, and energy are becoming increasingly critical. Temiz *et al.* developed a solar-powered centralized heating system for agriculture aimed at maximizing the efficient and effective use of resources.[6] Brown *et al.* analyzed and discussed three main electrical energy substitution technologies:

---

*Author for Correspondence
E-mail: sujuan@cau.edu.cn

electric vehicles, photovoltaic panels, and air source heat pumps.[7] Building on these analyses, Mboumboue *et al.* approached from a national perspective, conducting a survey in Cameroon to quantify the energy potential of agricultural, fishery, forestry, and livestock residues.[8] They considered the corresponding conversion systems and analyzed the significance of biomass as an energy source, providing a broader perspective on electrical energy substitution.

Scholarly investigation into the substitution of electrical energy within the fishery sector remains restricted; however, several studies have explored aspects of energy consumption and carbon emissions in this industry. Xu *et al.* used the LEAP model to analyze energy trends under different scenarios in their study on energy consumption and carbon emissions in fisheries.[9] Scroggins *et al.* compared the grid energy and electricity costs for different aquaculture species in the United States, finding that the energy demand of fisheries and aquaculture is influenced by their typically remote locations, production methods, and seasonal energy needs, requiring solutions tailored to specific circumstances.[10]

Current mainstream methods for predicting the potential of electrical energy substitution include the BP neural network model, particle swarm optimization, and support vector machines among various algorithms.[11,12] Li *et al.* based on the improved GRA-IPSO-BP model and quantitative indicators of factors influencing electrical energy substitution potential, predicted the electrical energy substitution volume in Zhejiang, China.[13] Lu *et al.* proposed a prediction model based on Lasso-XGBoost-Stacking, utilizing regression models to evaluate the weight of each quantified influencing factor, thereby predicting the potential for electrical energy substitution in Zhejiang, China. Current research focuses on predictions at specific regional or national levels, with fewer studies targeting specific industries.[14] In 2022, Ma *et al.* addressing the ultra-short-term prediction of traction loads in electric railway power control, designed a combined prediction method integrating Discrete Wavelet Transform (DWT), Temporal Convolutional Networks (TCN), and Particle Swarm Optimized Support Vector Regression (PSO-SVR).[15]

Although research on electrical energy substitution technologies has been increasingly in-depth, existing literature mainly focuses on evaluating the application of specific technologies in reducing carbon emissions in agriculture. However, these studies often overlook the particularities and complexities in industries such as fisheries. On one hand, the operational environment of marine fisheries, such as in ocean fishing, has characteristics like high salinity, high humidity, and high corrosion, which place higher demands on the technical stability of electric fishing vessels and related electrical equipment. On the other hand, the seasonal and regional distribution of fishery resources results in significant spatiotemporal fluctuations in electricity demand, posing challenges for the construction and operation management of power infrastructure. Furthermore, compared to terrestrial agriculture, fisheries also face certain differences in policies and subsidy mechanisms, requiring exploration and promotion of specific areas such as fishing vessel retrofit, electrification of heating, and electricity subsidies for aquaculture. These factors collectively contribute to the complexity and uniqueness of electrical energy substitution in fisheries, necessitating systematic research that considers technical levels, economic feasibility, and national industrial layout. Moreover, although existing predictive models have shown good applicability and accuracy in the quantitative assessment of electrical energy substitution potential, these models are mostly limited to regional or national-level analyses, leaving gaps in research for specific industries.

This paper focuses on the fisheries sector as a specific industry. First, it provides a comprehensive analysis of the unique technical, economic, and policy factors influencing the industry. Consequently, to navigate challenges such as limited data availability, condensed development timelines, and the inherent non-linearity of data in forecasting electrical energy substitution potential within the fishery sector, this study puts forth a predictive model integrating Particle Swarm Optimization (PSO) with Support Vector Regression (SVR). Finally, the method's predictive accuracy is validated through a case study, demonstrating significant improvement. The paper shows that the implementation of electrical energy substitution in China's fisheries sector is highly feasible.

Main Influencing Factors of Electric Energy Substitution

Technological Influence

Technology is the core driving factor for energy substitution in any industry. Relevant indicators include the penetration rate of electrical equipment and the energy efficiency of such equipment. The gross fishery production and related population can also reflect the technical level of the industry to a certain extent. As the technological level increases, the gross production value grows, which can also drive the growth of employment in the sector, while improving the level of electrification. Therefore, in this paper, the gross fishery production and fishery population are taken as technology-related influencing factors, with specific formulas shown in Eqs (1) & (2).

$$GDP_{sub}(t+1) = K_1 \cdot GDP_{sum}(t) \quad \text{... (1)}$$

where, $GDP_{sub}(t+1)$ represents the total GDP for the current year, K_1 is the elasticity coefficient of fishery GDP development, $GDP_{sum}(t)$ is the total GDP from the previous year,h is the contribution rate of fishery production.

$$G_{sub} = K_2 \cdot (R_1 - R)/\bar{R} \quad \text{... (2)}$$

where, G_{sub} is the population growth rate, K_2 is the elasticity coefficient for population growth, R_1 is the population at the end of the year, R is the population at the beginning of the year, $\bar{R}$ is the average population for the year.

Economic Influence

The economic benefits of energy substitution determine its promotion in the fishery sector. By quantifying the economic impact, the influence of economic factors on the potential of energy substitution can be analyzed. The main economic factors in the fishery sector that influence energy consumption and electricity consumption include the initial high costs of purchasing electric fishing boats, solar photovoltaic panels, and wind power generation equipment. However, from an operational cost perspective, electricity costs are much lower than traditional fossil fuels. Therefore, this paper quantifies the economic impact by analyzing the substitution of fossil fuel consumption in the fishery industry using the equivalent calorific value method, as calculated in Eq.(3).

$$T_1 = (q_i \times H \times \theta)/(H_e \times \theta_e) \quad \text{... (3)}$$

where, q_i is the terminal fossil energy consumption, H is the energy calorific value; θ is the average thermal efficiency of energy utilization, H_e is the electric calorific value and θ_e is the average thermal efficiency of electricity.

The calorific value of coal is taken as 22 J/kg with an average efficiency of 0.4; the calorific value of crude oil is 42 MJ/kg with an average efficiency of 0.5; and the calorific value of electricity is 3.6 MJ/kWh with an average efficiency of 0.9.

Policy Influence

Policies play a guiding and regulatory role in promoting energy substitution in the fishery industry. During the "14th Five-Year Plan" period, the policy suggests that newly installed renewable energy capacity will become the absolute majority of new installations, and energy investment will accelerate toward a green and low-carbon transition. This paper selects the ratio of fixed investment in electricity to fixed investment in energy as the quantitative indicator for the policy's impact on energy substitution, with the specific formula shown in Eq. (4).

$$G_r = K \cdot F_e/(F_e + F_i) \quad \text{... (4)}$$

where, G_r represents the proportion of new electricity generation, K is the elasticity coefficient, F_e is fixed investment in electricity, F_i is fixed investment in non-electric energy.

PSO-SVR Electric Energy Substitution Prediction Model

This paper introduces a specific formula to determine the extent of electric energy substitution, where the potential for such substitution is gauged by contrasting electrical energy usage with total energy demand. In forecasting electrical energy substitution, a Support Vector Regression (SVR) model is utilized, and its predictive capabilities are augmented by integrating Particle Swarm Optimization (PSO). This combined PSO-SVR methodology facilitates the effective refinement of SVR's crucial parameters, leading to an enhancement in prediction efficacy. Moreover, by leveraging a global optimization approach, the PSO-SVR model successfully mitigates the problem of local optima, thereby improving the reliability and precision of its predictions when applied to intricate and non-linear datasets.

Calculation of Electric Energy Substitution Amount

For the quantitative calculation of electrical energy substitution, let $E(t)$represent the total energy consumption in year t (in 10,000 tons of standard coal), and $D(t)$ represent the actual electrical energy consumption in year t (in 100 million kWh). Assuming the proportion of electric energy remains the same as in year t, the electrical energy substitution in year $(t+1)$, denoted as $D(t+1)$, is defined as the difference between the electrical energy consumption in year $(t+1)$ and that in year $(\boldsymbol{t})$, as shown in Eq. (5).

$$D_{sub}(t+1) = E(t+1) - D_{sum}(t+1) \cdot E(t)/D_{sum}(t) \quad \text{... (5)}$$

where, $D_{sub}(t+1)$ represents the electric energy substitution amount in year $(t+1)$,$E(t+1)$ denotes the actual electric energy consumption in the subsequent year, $D_{sum}(t+1)$ represents the total energy consumption in the subsequent year, $E(t)$ is the true electricity consumed during the present year, $D_{sum}(t)$ is the aggregate energy utilized during the present year

SVR Prediction Modeling

Support Vector Regression (SVR) exhibits significant advantages in addressing nonlinear relationships, analyzing high-dimensional data, and handling small sample sizes, and is notably robust; hence, it is particularly applicable in predicting the potential for electrical energy substitution, achieving considerable predictive accuracy. [16]The SVR algorithm employs nonlinear mapping to project input variables into a high-dimensional space, resulting in the linear regression function as shown in Eq. (6).

$$f(x) = \omega \cdot \varphi(x) + b \quad \text{... (6)}$$

where, $f(x)$ is the predicted value returned by the regression function, ω is the weight vector; $\varphi(x)$ is a high-dimensional nonlinear mapping function, b is the bias term; x is the input multidimensional data.

When employing the regression vector method, it is common to select linear, polynomial, or Radial Basis Function (RBF) kernels. In this study, the RBF kernel, as shown in Eq.(7), is chosen for its capability to handle complex nonlinear issues effectively.

$$K\left(x_i, x_j\right) = \exp\left(-x_i - x_j^2/2\sigma^2\right) \quad \text{... (7)}$$

where, σ is the parameter of the kernel function.

By setting the tolerance ε to define the maximum allowable deviation of data points from the regression function, we introduce Lagrange multipliers. The optimization objective is to minimize model complexity while ensuring that the regression function is as close as possible to the training data points within the given ε range, thus constructing the optimization problem to be solved as shown in Eqs (8) & (9).

$$\min 1/2\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad \text{... (8)}$$

$$\begin{cases} y_i - \omega\varphi(x_i) - b \le \varepsilon + \xi_i \\ -y_i + \omega\varphi(x_i) + b \le \varepsilon + \xi_i^*, i = 1,2,\cdots,k \\ \xi_i \ge 0, \xi_i^* \ge 0 \end{cases} \quad \text{... (9)}$$

where, ξ_i are slack variables,$C$is the regularization parameter, i represents the i-th sample, n is the total number of samples.

Particle Swarm Support Vector Regression

While Support Vector Regression (SVR) offers distinct benefits, it also presents challenges due to its computational intensity; furthermore, its effectiveness is critically dependent on the appropriate choice of its kernel function and associated parameters. Selecting these inappropriately can lead to a model that performs below its potential. To address this, Particle Swarm Optimization (PSO) provides a method to fine-tune crucial SVR parameters—including C, ε, and those of the kernel function—aiming to identify their most effective configuration. This optimization process markedly enhances SVR's predictive capabilities and accuracy.[16] PSO is a global optimization algorithm that effectively avoids local optimum issues, which traditional optimization methods might fall into. When handling complex and nonlinear data, PSO-SVR better adapts to the diversity and complexity of the data, making it particularly important for forecasting tasks involving electrical energy substitution potential, which involve multiple variables and complex relationships.

In the particle swarm optimization algorithm, the formulas for updating the velocity and position of particles are given in Eqs (10) &(11) respectively.

$$v_{sd}^{k+1} = pv_{sd}^{k} + c_1 r_1\left(P_{bestsd} - x_{sd}^{k}\right) + c_2 r_2 \left(G_{bestsd} - x_{sd}^{k}\right) \quad \text{... (10)}$$

$$x_{sd}^{k+1} = x_{sd}^{k} + v_{sd}^{k} \quad \text{... (11)}$$

where, v_{sd}^{k+1} is the updated velocity for the d-th particle after the (k+1)-th step, v_{sd}^{k} is the velocity of the d-th particle at the k-th iteration, $c_1$and c_2 are cognitive and social learning factors, r_1 and r_2 are random numbers; p is the inertia weight, P_{bestsd} is the personal best position of the d-th particle up to the k-th iteration, G_{bestsd} is the global best position found by any particle in the swarm up to the k-th iteration, x_{sd}^{k+1} represents the position of the d-th particle at the (k+1)-th iteration, x_{sd}^{k} is the position of the d-th particle at the k-th iteration.

By optimizing the parameters of SVR, PSO-SVR improves the model's fitting and generalization capabilities, thereby enhancing the accuracy and stability of electrical energy substitution predictions. The specific process is shown in Fig. 1.

Case Analysis of Electric Energy Substitution Potential in Fisheries

Data Processing and Parameter Setting

To assess the performance of the PSO-SVR model for cumulative electrical energy substitution, as detailed in this study, an investigation into the progression of electrical energy substitution within China's fishery sector over the last ten years was undertaken as a case study. Data from the China Statistical Yearbook and the China Fisheries Statistical Yearbook for 2012–2021 were reviewed, and a consistency check was performed on the multi-dimensional raw data. Records with significant outliers (such as minor data entry errors or missing records) were excluded, and missing values were filled using linear interpolation. The cumulative electrical energy substitution for China was then calculated, as shown in Table 1.

The historical data on electrical energy substitution from 2012 to 2016 were used as the training set. The original annual values of total fisheries output, population, total energy consumption, electrical energy consumption, and the proportion of new power investment were collected as independent variables, with electrical energy substitution volume serving as the dependent variable. The BP neural network algorithm, SVR method, and PSO-SVR method were respectively employed to predict the electrical energy substitution volume from 2017 to 2021.

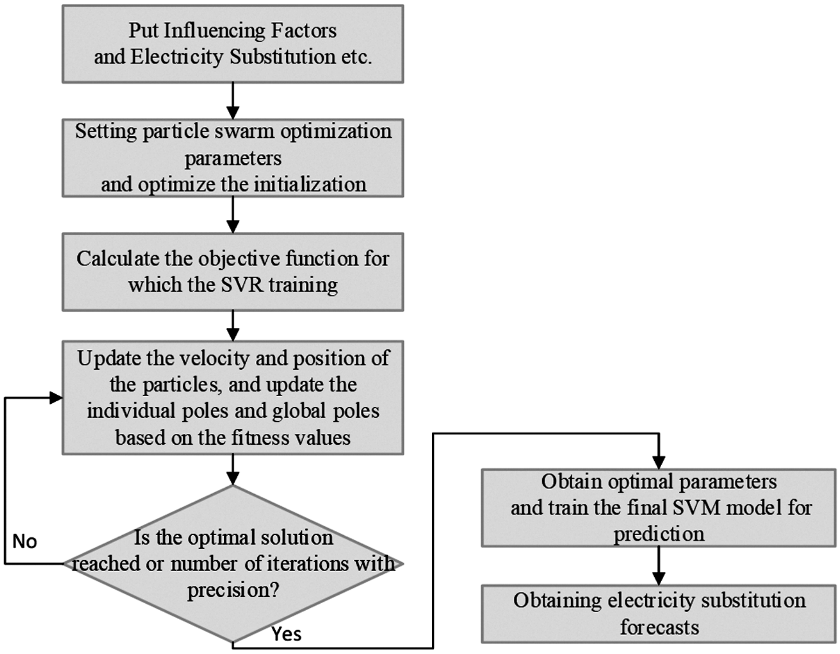

Fig. 1 — Flow chart of PSO-SVR predictive electricity substitution model

Table 1 — Data related to electricity substitution in China's fisheries, 2014−2021

Years	Gross fisheries product/billion dollars	Fishery population/million	Total fishery energy consumption (standard coal)/million tons	Electricity consumption in fishery/billion kWh	Proportion of new power investment in fisheries	Substitution of electric energy in fishery/tons of standard coal
2012	17321.88	2073.81	702.36	91.08	13.0%	−0.11
2013	19351.89	2065.94	724.95	92.43	12.7%	1.66
2014	20858.95	2035.04	721.8	91.17	12.6%	−0.86
2015	22019.94	2016.96	744.39	93.6	12.6%	2.99
2016	23662.29	1973.41	772.65	98.28	12.7%	3.44
2017	24761.22	1931.85	805.05	105.75	13.1%	3.35
2018	25864.47	1878.68	790.29	111.87	14.2%	8.06
2019	26406.50	1828.20	811.62	122.94	15.1%	8.05
2020	27543.47	1720.77	833.67	127.98	15.4%	6.20
2021	29689.73	1634.24	869.49	143.73	16.5%	10.25

Within the PSO-SVR model for predicting cumulative electrical energy substitution, the Particle Swarm Optimization (PSO) algorithm was utilized to refine both the penalty and kernel function parameters, employing a multi-objective optimization strategy. The population size in the PSO algorithm was set to 20, and the maximum number of iterations was 200. A linearly decreasing strategy was adopted for the inertia weight w, decreasing from 0.9 to 0.4. The acceleration constants c_1 and c_2 were both set to 2. If the global optimal fitness did not improve significantly after 200 consecutive iterations, the convergence condition was considered to be met and the iteration was terminated. The initial parameters obtained from the SVR model were used as the initial particle positions.

Experimental Results and Analysis

Based on the data from the five influencing factors mentioned above, BP neural network prediction model, PSO prediction model, and PSO-SVR prediction model were respectively used to fit the annual electrical energy substitution volumes in China's fisheries from 2017 to 2021 and the results are shown in Fig. 2

The prediction results of the PSO-SVR algorithm were relatively close to the actual values in each year, and the trends largely aligned with the original data. The SVR model was able to fit the early-stage data trend well, but its prediction deviation increased significantly in the later stages. The BP neural network model exhibited greater fluctuations in its early predictions, but the later results were very close to the actual data.

The BP neural network model has the advantages of a simple structure and ease of implementation, but it is prone to getting stuck in local minima during large-scale parameter training and has relatively slow training speed. Operating on the principle of structural risk minimization, the SVR model demonstrates robust generalization capabilities and holds distinct advantages when applied to limited datasets. Nevertheless, its efficacy is considerably influenced by the chosen kernel function and its associated parameters, and improper parameter selection may lead to a decrease in prediction accuracy. PSO-SVR optimizes the key parameters of SVR in the global space using the particle swarm algorithm, which can overcome the shortcomings of local search to some extent, achieving better convergence and prediction performance. However, PSO-SVR requires a relatively large computational load during the iterative process, making it more suitable for prediction tasks with smaller data sets. In summary, PSO-SVR has high application value in small sample prediction scenarios for electrical energy substitution in fisheries.

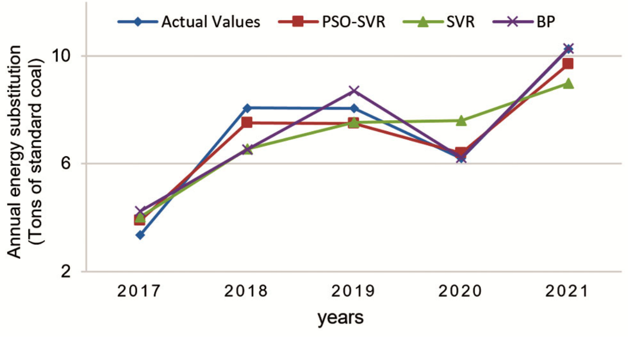

Fig. 2 — Comparison of predicted electric energy substitution values from three models with actual values

This study projected the electrical energy substitution potential for China's fisheries at two key future points, 2035 and 2050, by applying the PSO-SVR prediction model. The projections were grounded in the main indicators of the 14th Five-Year National Fishery Development Plan (Ministry of Agriculture and Rural Affairs, 2021) and an assessment of prevailing trends among factors influencing such substitution. Prediction of future electric energy substitution potential in fisheries for the year 2035 and 2050 and 28.86 and 39.74 tons of standard coal, respectively.

Projected figures indicate that the capacity for electrical energy substitution within the region is anticipated to attain 288,600 tons of standard coal by the year 2035, and subsequently expand to 397,400 tons of standard coal by 2050. These projections suggest that over the forthcoming decades, driven by the enforcement of policies aimed at energy conservation and emission mitigation in the fisheries sector, electrical energy substitution holds considerable promise for development and practical application within this industry.

Statistical Analysis

The average absolute error (MAE), mean square error (MSE), and mean absolute percentage error (MAPE) for the three models were calculated. The formulas for these calculations are presented as Eqs (12)-(14), respectively.

$$\text{MAE} = (1/n)\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad \text{... (12)}$$

$$\text{MSE} = (1/n)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad \text{... (13)}$$

$$\text{MAPE} = (100\%/n)\sum_{i=1}^{n}|\hat{y}_i - y_i/y_i| \quad \text{... (14)}$$

Table 2 — Comparison of prediction model performance metrics

Model	MAE	MSE	MAPE
BP neural network	0.771	1.01	39.15
SVR	0.93	1.06	0.94
PSO-SVR	0.43	0.23	0.65

where, n is the sample size, y_i is the i-th actual value, $\hat{y}_i$ is the i-th predicted value.

These metrics reflect the degree of deviation between the predicted values and the actual values. Compared to MAE, MSE amplifies the errors. MAPE represents the average percentage of prediction errors and is suitable for cases where the range of actual values varies significantly. The calculation results are shown in Table 2.

Compared to the BP neural network, the SVR model shows a significant decrease in MAPE (from 39.15 to 0.94). However, its MAE (0.93 for SVR vs. 0.771 for BP) and MSE (1.06 for SVR vs. 1.01 for BP) values are slightly higher, indicating a trade-off in performance across different metrics. In comparison to the SVR model, the proposed PSO-SVR model reduces the MAE, MSE, and MAPE values by 0.50, 0.83, and 0.29, respectively. This indicates that the PSO-SVR model has superior prediction accuracy and a better-fitting result. Although it does not have the advantage in computation time, the time difference can be considered negligible since predictions related to electrical energy substitution typically involve small sample sizes. In summary, the algorithm proposed in this paper demonstrates good fitting performance after optimizing parameter selection based on the particle swarm algorithm.

Conclusions

This paper details the establishment of a PSO-SVR model designed for the systematic prediction and in-depth analysis of prospects for electrical energy substitution specific to the fisheries sector in China. The findings demonstrate that this developed model exhibits substantially superior performance compared to conventional models, particularly in its predictive accuracy and operational stability. Despite the higher initial investments associated with electrical energy substitution technologies, their operational cost advantages over conventional energy sources will become increasingly apparent as these technologies are further promoted. The study only considered marine fisheries in China for sample collection. Future research could enhance the model's applicability by incorporating more data from both freshwater and marine fisheries across different regions to further analyze the potential for electrical energy substitution. Additionally, simulation studies could be conducted under various scenarios of technological advancement, economic growth rates, and policy environments to analyze trends in electrical energy substitution. Furthermore, this study provides a theoretical basis for formulating related policies and practical pathways. In the context of accelerating global energy transitions, this research not only holds theoretical value but also offers practical implications for the sustainable development of China's fisheries and the application of clean energy.

Acknowledgements

Funding for the authors was provided by Construction of a Multi-Entity Energy Supply System for Offshore Fish Farms and Research on Synergistic Operation Technologies under number 5400-202421218A-1-1-ZN.

References

1 Qu B, Liu C, Li D Z & Guo B Q, Research on the development strategy of electricity substitution under the target off "carbon neutral", *Power Demand Side Manag*, **23(02)** (2021) 1–9.

2 D'Armengol L, Castillo M P, Ruiz-MallénI & Corbera E, A systematic review of co-managed small-scale fisheries: Social diversity and adaptive management improve outcomes, *Global Environ Change*, **52** (2018) 212–225.

3 Yu H B, Chen J Y, Liu Q, Wang Y, Dou Z L, Su J & Du S H, Analysis and suggestions on the current situation of electrical energy substitution industry, *Power Demand Side Manag*, **22(03)** (2020) 2–7.

4 Wu J F, Su J, Du S H, Wei J & Chen X C, Application of electric energy substitution technology in agricultural carbon emission reduction, *Rural Electr*, **10** (2023) 61–67.

5 Dai S F, Li X J, Jiang C H, Zhang Q, Peng B, Ping J F & Ying Y B, Omnidirectional wind energy harvester for self-powered agro-environmental information sensing, *Nano Energy*, **91** (2022) 106686.

6 Temiz M & Dincer I, Development of concentrated solar and agrivoltaic based system to generate water, food and energy with hydrogen for sustainable agriculture, *Appl Energy*, **358** (2024) 122539.

7 Brown M A, Kale S, Cha M & Chapman O, Exploring the willingness of consumers to electrify their homes, *Appl Energy*, **338** (2023).

8 Mboumboue E & Njomo D, Biomass resources assessment and bioenergy generation for a clean and sustainable development in Cameroon, *Biomass Bioenerg*, **118** (2018) 16–23.

9 Xu X, Gui F & Zhao S, Simulation of fishery energy consumption and carbon emissions in Zhoushan City based on the long-range energy alternatives planning system model, *Front Energ Res*, **11** (2024) 1319915.

10 Scroggins R E, Fry J P, Brown M T, Neff R A, Asche F, Anderson J L & Love D C, Renewable energy in fisheries and

aquaculture: Case studies from the United States, *J Clean Prod*, **376** (2022) 134153.

11 Wang D M, Wang L & Zhang G M, Short-term wind speed forecast model for wind farms based on genetic BP neural network, *J Zhejiang Univ (Eng Sci)*, **46(05)** (2012) 837–841.

12 Zhu Y W, Shi X C, Dan Y Q,Li P, Liu W Y, Wei D B & Fu C, Application of PSO Algorithm in Global MPPT for PV Array, *Proc CSEE*, **32(04)** (2012) 42–48.

13 Li C Z, Niu D X, Zhang X Y & Miao B, Zhejiang province electric power substitution potential prediction model based on improved particle swarm optimization BP neural network, *Sci Technol Eng*, **20(13)** (2020) 5173–5179.

14 Lu C G, Ge M L, Song L, Wu J L & Pan G P, A prediction method for provincial power substitution potential based on Lasso-XGBoost-Stacking, *Zhejiang Electr Power*, **42(09)** (2023) 9–16.

15 Ma Q, Wang H, Luo P & Li Q R, Ultra-short-term Railway traction load prediction based on DWT-TCN-PSO-SVR combined model, *Int J Electr Power Energy Syst*, **135** (2022) 107595.

16 Sun Y, Shi M, Shan B G & Cao F, Electric energy substitution potential analysis method based on particle swarm, optimization support vector machine, *Power Syst Technol*, **41(06)** (2017) 1767–1771.