

## Research Article

# China's Energy Demand Forecasting Based on the Hybrid PSO-LSSVR Model

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Forecasting energy demand accurately is the basis for the formulation and implementation of energy planning. In this paper, energy demand influencing factors are mainly decomposed into scale economy effect, population size effect, energy structure effect, and residential consumption effect based on the Logarithmic Mean Divisia Index (LMDI). Then, the Cointegration and Granger Causality tests are used to discover the influencing factors of energy demand in China. On this basis, a hybrid optimization algorithm, the least-squares support-vector regression optimized by particle swarm optimization (PSO-LSSVR), is proposed to forecast the energy demand of China. Then, three scenarios are set up to analyze the further development of drive factors of energy demand. Finally, in accordance with the forecasting results, some suggestions related to China's energy development policy are given. The main results are as follows. First, gross domestic product (GDP), the total population at the end of the year (POP), the coal consumption ratio in energy (CCR), and residential consumption levels (RCLs) are dominant indicators of energy demand in China. Second, the improved PSO-LSSVR model has significant superiority than other models in energy demand forecasting, a complex and nonlinear system with small samples. Third, China's energy demand will peak in 2022, which is 4.9 million tce in all scenarios.

## 1. Introduction

**1.1. Background, Purpose, and Significance.** Energy, the material basis for economic development and social progress, has gained considerable attention. Energy demand forecasting has a guiding significance on the formulation and implementation of energy policy. Driven by technological advances and sustainable development, the global energy supply became cleaner and lower carbon. In response to reducing carbon emission and combating climate change, the global economy started to transit its structure towards a low-carbon economy. At the same time, the global energy market began to enter a new period of energy transition. Correspondingly, China has also gradually entered the period of energy structure adjustments and transformation upgrading. China, as the largest developing country, has the largest total energy consumption in the world. BP Statistical Review of World Energy (2020) reports that China's energy demand growth accounts for more than three-quarters of net global energy consumption, while the US

and Germany posted the largest declines influenced by COVID-19. Therefore, the transformation of the energy consumption structure in China can affect the global energy consumption structure. The overwhelming growth of energy consumption in China will lead to an imbalance between energy supply and demand. Similarly, this problem can occur in other developing countries. Hence, forecasting the accurate energy demand in China plays a decisive role in formulating and implementing energy policy and provides enlightenment and reference significant for other developing countries. However, the existing research on the prediction model of energy demand is weak, so this paper focuses on the prediction model suitable for an energy system.

**1.2. Current Research.** A lot of scholars have studied energy demand prediction. The core part of it can be divided into two strands. The first strand is the selection of indicators. Energy is a nonlinear complex system influenced by complex socioeconomic factors, according to the existing literature devoting to identifying the factors affecting energy

demand. For instance, Xia and Wang found the factors of energy demand mainly included gross domestic product (GDP), population, urbanization rate, and energy consumption structure by the Logarithmic Mean Division Index (LMDI) [1]. Wu and Peng hold the view that economic growth, total population, investment in fixed assets, energy efficiency, energy structure, and household energy consumption per capita are the most critical elements of energy demand [2]. For higher forecasting accuracy, the most suitable indicators are picked out as the forecasting inputs.

The second strand is the forecasting models, including the univariate model and multivariate model. The univariate method propels further prediction with historical data, such as the gray model, ARIMA model, and the like [3, 4]. The multivariate method is based on the determined mapping relationship between energy demand (dependent variable) and independent variables. Also, the commonly used prediction models are multivariate methods, such as the multiple linear regression (MLR) model and partial least-squares regression model [5, 6]. The univariate model applies primarily to short-term prediction, and the multivariate model is more suitable for medium- and long-term prediction.

Artificial intelligence (AI) methods have been extensively used for forecasting due to their nonlinear mapping ability and good forecast ability. The artificial neural networks (ANNs) [7], support vector machine (SVM) [8], and extreme learning machine (ELM) [9] are all widely used AI methods. At the same time, the optimal parameters of the prediction model can be found by the heuristic algorithm. The heuristic algorithm is good at giving feasible solutions to combinatorial problems to be solved. Cui et al. construct a new prediction model based on back propagation neural network with the optimization of GA algorithm and PSO algorithm [10]. The commonly used heuristic algorithms are particle swarm optimization (PSO) [11], ant colony optimization (ACO) [12], genetic algorithm (GA) [13], etc.

The energy system is complex and lack of samples; there will be insufficient training, unstable performance, and over “learning” in ANNs. All of these will lead to unsatisfactory prediction results. SVM, proposed by Cortes and Vapnik [14], has an excellent performance in solving small samples, nonlinear, high dimension problems. Therefore, SVR, the regression version of SVM, is widely used in various energy research. Suykens and Vandewall [15] improved LSSVR in 1999, the least-squares formulation of SVR, which has better generalization abilities and robust computation. Kaytez et al. [16] find that LSSVR has better accuracy than regression analysis and neural network in long-term electricity consumption prediction. However, there are still difficulties in LSSVR including the choice of kernel and regularization parameters, so PSO is introduced to improve the prediction accuracy of LSSVM. Although PSO-LSSVR has been employed in other fields successfully [17], the application of PSO-LSSVR in energy demand forecasting is quite a few. Therefore, it contributes to making energy demand prediction abundant.

**1.3. Main Aim and Principle Conclusions.** This study is aimed at solving the following problems. First, identify dom-

inant indicators of energy demand to describe and analyze the complex features of the energy system in China. Second, hunt for a prediction model with high-precision ability to reasonably predict energy demand’s trend in China. Third, analyze the changing trend of energy demand under different development scenarios produced by other development policies. Forth, according to the determined vital factors, predict the movement of energy demand in different situations, and give corresponding policy suggestions for energy development.

The principle conclusions lie in the following aspects. First, this paper finds that GDP, population (POP), coal consumption ratio (CCR), and residential consumption level (RCL) are the critical factors of the energy demand of China through the Cointegration and Granger Causality test. Second, a hybrid forecasting model, PSO-LSSVR, was first proposed to forecast energy demand in this paper. Additionally, the established model shows a much better effect on the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the goodness of fit ( $R^2$ ) compared with traditional models. Third, scenario analysis sets three different scenarios to analyze the energy demand trend in China under different levels to formulate corresponding energy development plans and policies.

The remainder of this paper is arranged as follows. The method of this paper is introduced in Section 2. Section 3 discussed China’s energy demand influencing factors through the Cointegration and Granger Causality tests. The energy demand prediction model, PSO-LSSVR, is proposed in Section 4. In Section 5, the possible trend of energy demand under different development scenarios is analyzed in detail. Section 6 depicts the key conclusions. Forecasting mechanism for energy demand is listed in Figure 1.

## 2. Methodology

**2.1. Least-Squares Support-Vector Regression Model.** SVM, proposed by Cortes and Vapnik [14], converts the input space into a high-dimensional space through nonlinear mapping and finds the optimal hyperplane to divide the feature space in this space based on SVC and statistical learning theory. However, SVM takes too much time to cope with thousands of data. Therefore, least-squares support-vector machine (LSSVM) was proposed [15]. Compared with SVM, LSSVM has more advantages [18] as follows:

- (i) It changes the structure of the loss function, taking a squared loss function rather than it in SVM
- (ii) It transforms inequality constraints into equality constraints, avoiding solving QP problems when finding the optimal hyperplane

With these modifications, the computational quantity is reduced heavily, and training speed is also significantly accelerated.

Support vectors can be used in SVC for classification and in SVR for regression. Therefore, LSSVM can be categorized into LSSVC for classification and LSSVR for regression

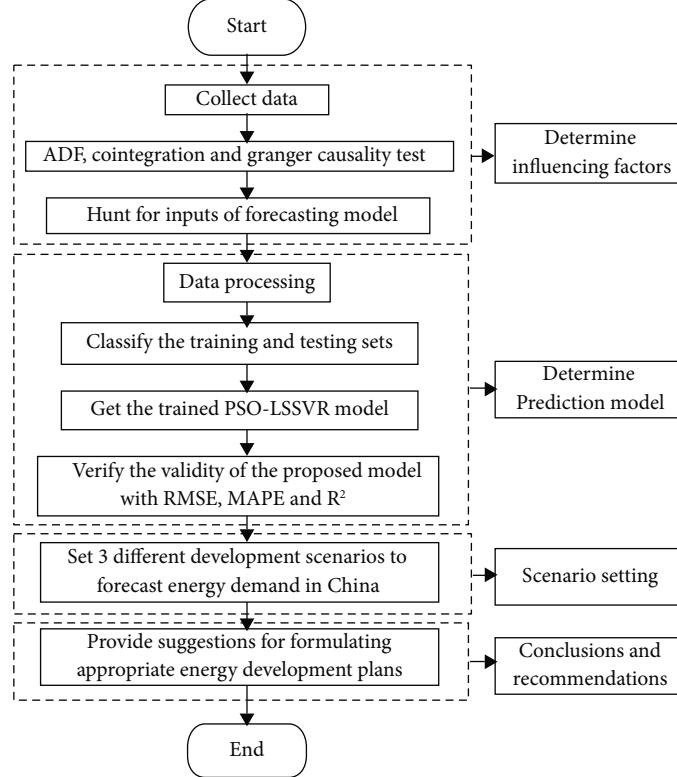


FIGURE 1: Forecasting mechanism of energy demand.

purposes. LSSVR is a nonlinear regression model based on SVC and structural risk minimization. Then, SVR and LSSVR will be introduced. The principle of LSSVR is described briefly.

Given a set of training sample points:  $S = \{(x_k, y_k) | k = 1, 2, \dots, n\}$ , where  $x_k \in R^n$  is the input value and  $y_k \in R$  is the output value. By the map  $\Phi(\bullet)$ , the samples from the original space  $R^n$  is mapped into the feature space  $\varphi(x_k)$ . The optimal decision function is defined.

$$y(x) = \omega^T \varphi(x) + b, \quad (1)$$

where  $\varphi(x)$  is the kernel function,  $\omega$  is the weighted vector, and  $b$  is a constant.

Then, the regression problem can be transformed into an optimization problem with constraints.

$$\min_{\omega, b, e} J(\omega, e) = \frac{1}{2} \omega^T \omega + \frac{1}{2} \gamma \sum_{k=1}^n e_k^2 \text{s.t. } y_k = \omega^T \varphi(x_k) + b + e_k, \quad (2)$$

where  $k = 1, 2, \dots, n$ ,  $\gamma$  is the regularization parameter, and  $e_k$  is the slack variable. To solve the equation, the Lagrange function is defined.

$$L(\omega, b, e, \alpha) = J(\omega, e) - \sum_{k=1}^n \alpha_k [\omega^T \varphi(x_k) + b + e_k - y_k], \quad (3)$$

where  $\alpha_k$  is the Lagrange multiplier. After the calculation, the values of  $\alpha$  and  $b$  are determined. Then, the fitting function can be represented.

$$f(x) = \sum_{k=1}^n \alpha_k K(x, x_k) + b, \quad (4)$$

$$K(x, x_i) = \varphi(x)^T \cdot \varphi(x),$$

where  $K(x, x_i)$  is the kernel function, which expresses non-linear mapping.

The kernel function decides the mapping function and feature space. The Radial Basis Function (RBF) can grapple with the amount of input data efficiently, and it is suitable for theoretical analysis owing to its good analyticity. Thus, RBF is the kernel function in this paper, and it is defined.

$$K(x, x_i) = \exp \left( \frac{-\|x - x_i\|^2}{2\sigma^2} \right), \quad (5)$$

where  $x$  is an  $m$ -dimension input vector.  $x_i$  is the centre of the  $i$ th RBF.  $\sigma^2$  is the length of the kernel function.  $\|x - x_i\|$  is the norm of a vector.  $\gamma$  and  $\sigma^2$  are crucial to ensure prediction accuracy and model generalization ability in LSSVR.

**2.2. Particle Swarm Optimization Algorithm.** The PSO, simulating the hunting activities of birds and fish, is a random search algorithm [19], which can find the optimal global

solution. The corresponding relationship between PSO and bird hunting activities is described in Table 1.

PSO is initialized with a random population including  $m$  particles, which is  $X = \{X_1, X_2, \dots, X_m\}$ . Each particle is not only a point in a  $D$ -dimension space but also a feasible solution in the solution space. Particles change their position by flying in the solution space until arriving at the optimum.  $X_i = \{x_{i1}, x_{i2}, \dots, x_{id}\}$  is the  $i$ th particle's position.  $V_i = \{v_{i1}, v_{i2}, \dots, v_{id}\}$  ( $i = 1, 2, \dots, m$ ) is the  $i$ th particle's velocity, which depends on three components as follows:

- (1) The inertia term:  $w * v_{id}(k)$ . It is affected by the constant inertia weight  $w$  and previous step velocity term  $v_{id}(k)$
- (2) The cognitive learning term:  $c_1 r_1 * (P_{\text{best}}(i) - x_{id}(k))$ . It is the distance between the local best position  $P_{\text{best}}(i)$  and the particle's position  $x_{id}(k)$
- (3) The social learning term:  $c_2 r_2 * (G_{\text{best}} - x_{id}(k))$ . It is the distance between the global best position  $G_{\text{best}}$  and the particle's position  $x_{id}(k)$

Thus, the velocity and position of the  $i$ th particle of iteration  $k$  are computed.

$$\begin{aligned} v_{id}(k+1) &= w \cdot v_{id}(k) + c_1 r_1 \cdot (P_{\text{best}}(i) - x_{id}(k)) - c_2 r_2 \cdot (G_{\text{best}} - x_{id}(k)), \\ x_{id}(k+1) &= x_{id}(k) + v_{id}(k+1), \end{aligned} \quad (6)$$

where  $r_1$  and  $r_2$  are two random numbers in the range of  $[0,1]$ ,  $c_1 = 1.7$  and  $c_2 = 2$  are acceleration coefficients, and  $w$  is the inertia weight factor determined by

$$w = w_{\max} - (w_{\max} - w_{\min}) \frac{n_i}{n_{\max}}. \quad (7)$$

The procedures involved in PSO implementation are given as follows:

- (1) Set the parameters of the PSO algorithm, such as particle swarm size, inertial weight factor  $w$ , learning factor  $c_1$  and  $c_2$ , and random number  $r_1$  and  $r_2$
- (2) Initialize the velocity and position of particles randomly
- (3) Compute the fitness of the  $i$ th particle and obtain the local best position  $P_{\text{best}}(i)$  and the global best position  $G_{\text{best}}$
- (4) Update the local best position  $P_{\text{best}}(i)$  and the global best position  $G_{\text{best}}$
- (5) Update the velocity and position of the particles
- (6) If the end condition is met, we can get the global best position; otherwise, we can return to step 3

**2.3. The PSO-LSSVR Model for Energy Demand Forecasting.** Different parameters as input combinations in LSSVR can produce various forecasting accuracy. Therefore, more

importance is focused on the PSO-LSSVR model for it can select optimization parameters automatically. The number, position, and velocity of particles and other parameters in the proposed model have been introduced in Sections 2.1 and 2.2. The proposed hybrid model selects the goodness of fit ( $R^2$ ) for finding the optimal kernel parameters  $\sigma^2$  and regulation parameter  $\gamma$ . It is conducive to improve prediction accuracy and reduce model uncertainty and randomness. Figure 2 depicts the specific details of the proposed PSO-LSSVR model.

### 3. Data Resource and Driving Factor Preselection

**3.1. Data Resource.** All data used in this paper are obtained from China Statistical Yearbook 2020 [20]. This paper measures GDP in  $10^2$  billion yuan (in constant 1990 price in China). The total population at the end of a year is measured at  $10^2$  million. The energy consumption structure is indicated by the coal consumption ratio in total consumption. Residential consumption levels (in constant 1990 price in China) are measured at  $10^2$  yuan. And the energy demand is measured at Mtce (million tons coal equivalent).

#### 3.2. Driving Factor Preselection

**3.2.1. Factors Affecting Energy Demand of China.** After research, we found that energy demand influencing factors can mainly be decomposed into scale economy effect, population size effect, energy structure effect, and residential consumption effect [21].

Scale economy effect is that economic growth explains the chief changes in energy demand. It was first proposed that changes in GNP caused energy demand to fluctuate, but the long-term Cointegration cannot be found in the United States [22]. Energy demand is mainly affected by economic growth in two aspects. Firstly, economic growth is the driving force for energy development, and it provides the market for energy development. Therefore, economic growth fuels energy demand. Secondly, energy is the core and power source of developing productive social forces. Guaranteeing energy demand is the premise for promoting social economy development stably. At the same time, GDP is a crucial indicator of economic growth. Correspondingly, the floating of GDP will make energy demand floating.

The population size effect is that population growth can affect energy demand markedly [23]. China is a populous country, and the population ranks first in the world in 2019 with the total population reaching 1.4 billion. BP Statistical Review of World Energy (2021) [24] shows that China was one of the few countries where energy demand increased in 2020. China's total energy consumption ranked first in the world in 2019. However, energy consumption per capita was 2.836 tons of standard coal, only reaching the world average level. The population size affects total energy consumption and energy occupancy per capita directly. Therefore, POP is considered as an indicator affecting energy demand in this paper.

TABLE 1: The corresponding relationship between PSO and bird hunting activities.

Bird hunting activities	Particle swarm optimization
Bird flock	A set of valid solutions in a search space
Hunting space	Problem search space
Flying speed	The velocity vector of the solution
The location of the birds	The position vector of the solution
Individual cognition and group collaboration	Update the velocity and position
Finding food	Finding the optimal global solution

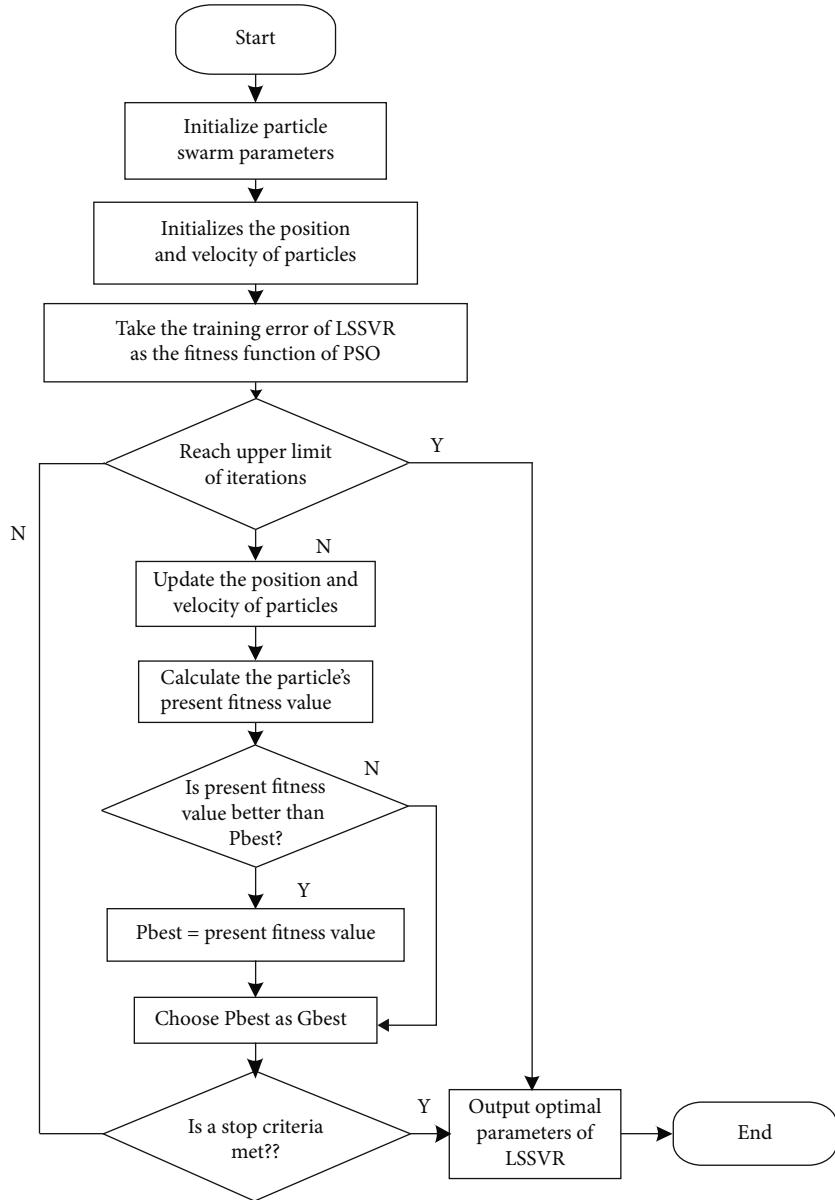


FIGURE 2: The improved PSO-LSSVR model.

The energy structure effect is that various energy types have different energy efficiency, and low energy efficiency will lead to high energy consumption. Energy consumption structure reflects the ratio of various energy resources in pri-

mary energy consumption directly [25]. Coal-based energy consumption structure has low utilization efficiency and high environmental pollution. Since the 1990s, China has been the largest producer and consumer of coal globally,

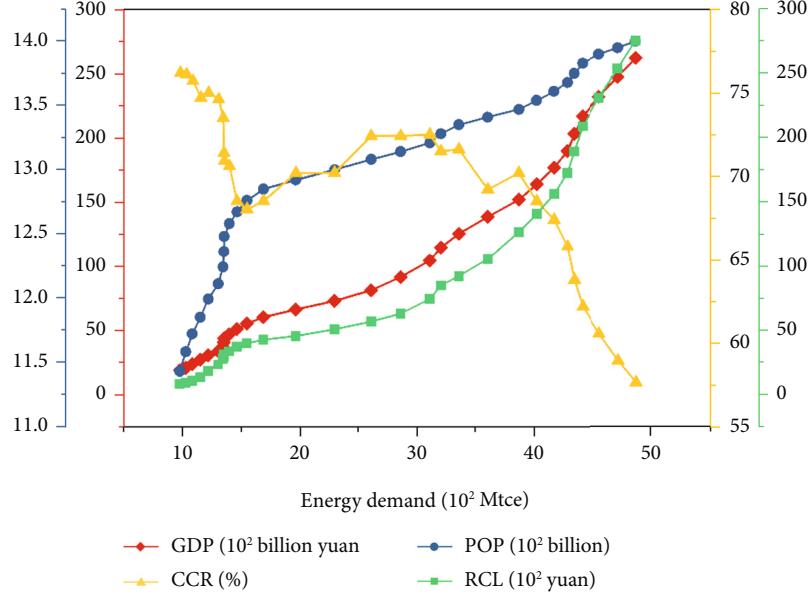


FIGURE 3: Relation among GDP, POP, RCL, CCR, and energy demand.

TABLE 2: ADF test.

Time series	<i>t</i>	Critical value of 0.05	<i>p</i>	Conclusion
ED	-0.23	-2.972	0.935	Nonstationary
GDP	3.547	-2.941	1	Nonstationary
POP	-2.395	-2.972	0.143	Nonstationary
CCR	-0.192	-2.976	0.939	Nonstationary
RCL	1.161	-2.981	0.996	Nonstationary
D (ED, 2)	-4.147	-2.976	0.001**	Stationary
D (GDP, 2)	-8.273	-2.944	0.000***	Stationary
D (POP, 2)	-4.801	-2.981	0.000***	Stationary
D (CCR, 2)	-10.992	-2.976	0.000***	Stationary
D (RCL, 2)	-3.449	-3.042	0.009**	Stationary

TABLE 3: Unrestricted Cointegration rank test (trace).

Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Prob.**
None*	0.987905	242.9389	69.81889	0.0000
At most 1*	0.917747	128.1496	47.85613	0.0000
At most 2*	0.785139	63.20264	29.79707	0.0000
At most 3*	0.573033	23.22072	15.49471	0.0028
At most 4	0.041184	1.093446	3.841466	0.2957

Trace test indicates 4 cointegrating equations at the 0.05 level. \* denotes rejection of the hypothesis at the 0.05 level. \*\*MacKinnon-Haug-Michelis (1999) *p* values.

and 70% of China's total energy demand roots in coal consumption during 1990-2015 [26]. For sustainable development, China has been focused on optimizing energy consumption structure, reducing the ratio of coal, and increasing clean energy. Therefore, in the quantitative analysis of energy demand, CCR is selected as a factor influencing the trend of energy demand in this paper.

The residential consumption effect is that RCL reflects economic growth and the improvement of residents' living standards. The RCL plays a manifold impact on energy demand. It affects the energy demand not only directly but also indirectly through influencing industrial structure. According to Maslow's needs hierarchy theory, with the improvement of RCL, residents will increase the consumption of clean energy such as natural gas and electricity, etc., and reduce the consumption of traditional energy such as firewood and honeycomb coal. Hence, RCL is a vital factor influencing energy demand.

In summary, the energy system is a nonlinear system influenced by many factors, and various influencing factors have discriminative effects on energy demand [27]. The factors can be expressed by the following indicators: GDP, POP, CCR, and RCL. As shown in Figure 3, there is obvious positive correlation between GDP, POP, RCL, and energy demand, respectively. There are positive relationships among GDP, POP, RCL, and energy demand and negative relationships between CCR and energy demand. Conversely, it is an inverse correlation between CCR and energy demand. Therefore, these factors do promote or restrain the energy demand to some extent.

**3.2.2. The Unit Root Test and Cointegration Test.** For preventing the occurrence of spurious regression, the Granger Causality test will be used to confirm the causal relationship between China's energy demand and the factors identified above before forecasting energy demand. The Granger

TABLE 4: Results of Granger Causality tests.

Null hypothesis	Lag	F-statistic	Prob.
GDP does not Granger Cause ED	1	7.499	0.011
ED does not Granger Cause GDP		13.692	0.001
POP does not Granger Cause ED	1	7.527	0.011
ED does not Granger Cause POP	1	11.121	0.003
CCR does not Granger Cause ED	1	0.034	0.856
ED does not Granger Cause CCR	1	2.515	0.025
RCL does not Granger Cause ED	1	5.346	0.029
ED does not Granger Cause RCL	1	12.424	0.002

ED means energy demand.

TABLE 5: Typical MAPE values for evaluation.

MAPE (%)	Rank
$\leq 10\%$	High-accuracy
$10\% < \text{MAPE} \leq 20\%$	Good
$20 < \text{MAPE} \leq 50\%$	Reasonable
$> 50\%$	Inaccurate

Causality test requires that the series is stable or cointegrated. Thus, the unit root test (ADF) and Cointegration test will be implemented under the environment of Eviews 9.0 firstly.

Engle and Granger [22] put forward that the Cointegration relationship can be established when all independent series are integrated of the same order, or their linear relationship is stationary series. Therefore, before the cointegration analysis, it is necessary to judge the smoothness of variable series. The most common methods are the intuitive scatter plot method, autocorrelation function, and ADF test [22].

The null hypothesis of the ADF test refers to that the time series is nonstationary. There are two paths to ensure the time series is stationary. One is the  $p$  value less than 0.05 (or 0.01), the other is the  $t$  value less than the critical value of 0.05 (or 0.01). As shown in Table 2, in the first line,  $p = 0.935$  means refusing the null hypothesis that energy demand is a nonstationary sequence; in the sixth line,  $p = 0.001$  means accepting the null hypothesis that second-order difference energy demand is stationary. The conclusion shows that original sequences are nonstationary, and second-order difference sequences are stationary. Then, the Cointegration test can be done further.

Then, the Cointegration test is employed to judge if there exists a Cointegration relationship or long-term equilibrium relationship. The EG Cointegration test is often applied to test a single Cointegration relationship, and the Johansen Cointegration test is often used to test multiple Cointegration relations. The Johansen Cointegration test [28] is mainly divided into two steps. First, the least-squared estimation is conducted to calculate the equilibrium error and obtain the Cointegration regression. Second, the ADF test is carried out for the residual sequence. There exists a Cointegration relationship if the residual sequence is stable. It should be noted that the critical value or the  $p$  value in

Eviews 9.0 cannot be applied to determine whether the residual series is steady directly. It is necessary to calculate the corresponding crucial value according to the Cointegration regression threshold table.

As shown in Table 3, the optimal lag order of VAR is 3. “At most 4” in the table means there are at most four Cointegration relationships. However, the corresponding  $p$  value is 0.2957, less than 0.05, indicating rejection of the null hypothesis. Therefore, the results of the trace test reveal three Cointegration relationships existing among energy demand and its affecting factors in the 5% significance level. Consequently, although our variables are nonstationary, there are long-term stable equilibrium relationships among them, so we can further carry out the Granger Causality test.

**3.2.3. Granger Causality Test.** Johansen’s Cointegration test shows the existence of a long-term equilibrium relationship among objectives determined in this study. However, it is not sure if this relationship is causality. Therefore, it is necessary to carry out the Granger Causality test [29] to analyze if there is Granger Causality between energy demand and its affecting factors. The Granger Causality test can be affected by the lag phase considerably. This paper determines the VAR model’s optimal lag order by multiple testing with different lags and AIC criteria. In addition, what needs to be noted is that Granger Causality is not a causal relationship in actual economic activities but the predictive ability of the variables’ lag value to the explained variable.

Avoiding spurious regression, the data participating in the Granger Causality test must be stationary series. The Granger Causality test, conducted on the stable data after treatment, between energy demand and its influencing factors in China is shown in Table 4. As seen in the first line of Table 5, the null hypothesis is “GDP does not Granger Cause ED,” and the  $p$  value is less than 0.05, which means that “GDP is the Granger Cause of ED,” refusing the null hypothesis. The Granger Causality test result shows that the GDP, POP, RCL, and energy demand were the bilateral causality except for CCR when the significance level was 5%, and the lag phase was 1. CCR and energy demand are one-way causalities. Thus, the influencing factors screened, GDP, POP, CCR, and RCL, do have a statistical causality with the energy demand in China. They are reasonable inputs for predicting the energy demand of China in PSO-LSSVR mode.

#### 4. Forecasting Energy Demand Based on PSO-LSSVR

**4.1. Data Preprocessing.** According to the above analysis, this paper selects the data of China’s energy demand and related factors from 1990 to 2019 for prediction, so there are 30 sample data. Before the datasets were used to train the PSO-LSSVR model, the data needed to be linear normalized, and after the forecasting process, the data was required to be antinormalized. The data can be linear normalized to the range  $[0, 1]$  by the following formula:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \quad (8)$$

where  $x'$  is the normalized data,  $x_{\max}$  is the maximum in data, and  $x_{\min}$  is the minimum in data.

**4.2. Performance Criteria.** The evaluation of the models is done according to three widely used error indexes: Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and  $R^2$ . MAPE describes the accuracy of prediction results. RMSE measures the deviation between the observed value and the actual value.  $R^2$  reflects the reliability of the regression model to explain the change of dependent variables. They are expressed by the following equations:

$$\begin{aligned} \text{MAPE} &= \frac{1}{N} \sum_{k=1}^N \left| \frac{y(k) - \hat{y}(k)}{y(k)} \right|, \\ \text{RMSE} &= \sqrt{\frac{1}{N} \sum_{k=1}^N (y(k) - \bar{y})^2}, \\ R^2 &= 1 - \frac{\sum_{k=1}^N (y(k) - \hat{y}(k))^2}{\sum_{k=1}^N (y(k) - \bar{y})^2}, \end{aligned} \quad (9)$$

where  $y(k)$  and  $\hat{y}(k)$  ( $k = 1, 2, \dots, N$ ) are the actual value and forecasting value, respectively. And  $\bar{y}$  is the average of the actual value.

MAPE is one of the criteria to judge the performance of the forecasting model. Table 5 shows the rank of MAPE. The smaller the MAPE value, the better the forecasting model. When MAPE is less than 10%, it means that the prediction model has high accuracy; when MAPE is greater than 10% but less than 20%, it means that the prediction model is good; when MAPE is greater than 20% but less than 50%, it means that the prediction model is reasonable; last, when MAPE is greater than 50%, it means that the prediction model is inaccurate, and it is irrational to forecast with the established model.

**4.3. Experimental Results and Analysis.** The GM (1,1), Multiplayer Linear Regression (MLR), LSSVR, and PSO-LSSVR are implemented to forecast China's energy demand based on the observations data from 1990 to 2019 in Matlab2017a programing language.

In the PSO-LSSVR model, the most important thing is to search out the best parameters. PSO has three parameters that need to be set in advance. The size of the number of particles  $N = 20$ , the acceleration coefficients  $c_1 = 1.5$  and  $c_2 = 1.7$ , and the number of maximal iterations  $I = 60$ . The best suitable parameters of LSSVR selected by PSO at about generation 20 are regularization parameter  $\gamma = 179.4585$  and kernel parameter  $\sigma^2 = 0.1842$ . And then, to ensure the stability of the results, even year data are used as training set, and odd year data are used as testing set. Figure 4 shows the error of training set and testing set.

To further compare the precision of different forecasting models, the MAPE, RMSE, and  $R^2$  are introduced. The comparison results are listed in Figure 5 and Table 6. Obviously, PSO-LSSVR is the optimal model to forecast China's energy demand, and LSSVR has the same excellent ability if you

have correct parameters, GM (1,1) worst. On account of that, LSSVR has advantages when dealing with nonlinear and dynamic features in the system. The conclusions both indicate that multivariate prediction models, such as MLR and LSSVR, have essential superiority than univariate time series prediction models in prediction, such as GM. Since time series prediction is easily affected by external environmental causing deviation. At the same time, the energy system is nonlinear and complex, and the multivariate prediction model will be well suitable for it.

Above all, based on a comprehensive comparison of MSE, MAPE, and  $R^2$ , the PSO-LSSVR model shows a satisfactory performance with high predictive accuracy and less predictive time than other models. Thus, it is applied to further predict China's energy demand in 2020-2025 for providing a basis of energy system's development and the achievement of carbon-neutral at an early date.

## 5. Forecasting China's Energy Demand in Different Scenarios

**5.1. Scenario Setting.** For accurate prediction, the development of factors affecting the energy demand of China has been analyzed in this section. It will set up three scenarios for China's growth in the future. Scenario A is the baseline scenario in which variables change in the same rate as what happened before. Scenario B is the lagging scenario relative to scenario A, in which variables change negatively. Scenario C is the priority scenario relative to scenario A, variables change at a positive rate.

**5.1.1. GDP.** GDP is an effective indicator of national economic growth. China's GDP is constantly growing from 1887 billion in 1990 to 74413 billion in 2019, and its growth rate continued to decline, and the growth rate gradually slowed down after 2010. Nowadays, there are a lot of scholars and institutions who analyze China's economic growth. Such as HSBC Bank thinks China's economic growth rates will be 5.5% during 2021-2030, 4.4% during 2031-2040, and 4.1% during 2041-2050, respectively [30]. Similarly, IMF latest reported that considering the impact of COVID-19, the annual growth rate of the global economy will be 6.0% in 2021 and 4.9% in 2022, respectively [24]. According to the "National Economic and Social Development Report," the economic growth rate in 2020 is 2.3% [23]. Given the COVID-19 and vaccination rate, China's economic growth is expected to back to 6.3% in 2021. Therefore, the GDP growth rate in 2020-2025 is set as 5.6% in scenario A, 5.8% in scenario B, and 6% in scenario C, respectively.

**5.1.2. Total Population.** Population growth is affected by both mortality and birth rates. The mortality rate is relatively stable. Therefore, population growth is mainly affected by the birth rate [31]. From 2012 to 2015, the population growth rate was steady at about 0.51% per year. After the implementation of the two-children policy in 2015, the population growth rate reached 0.58 in 2016. With child cost increasing and urban life accelerating, the birth rate

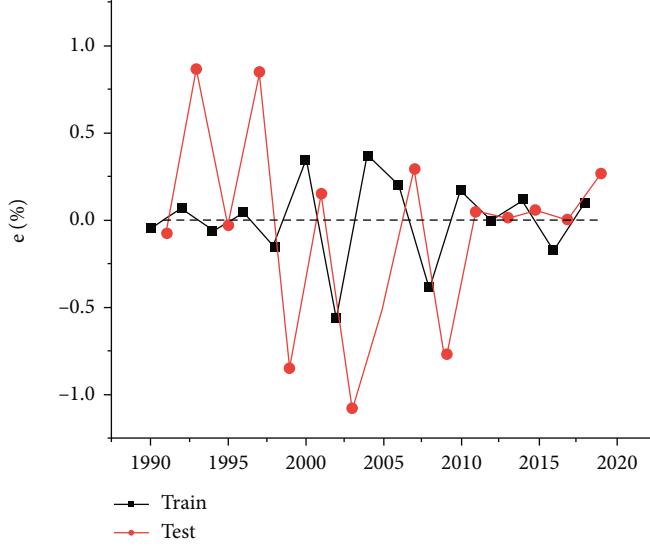


FIGURE 4: Errors of the training and testing set.

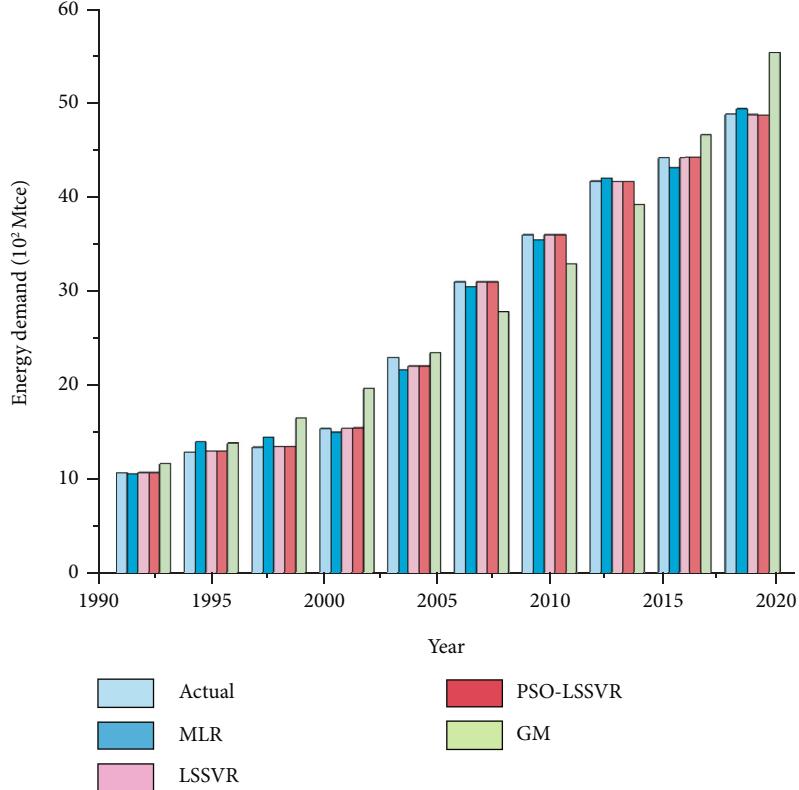


FIGURE 5: Comparison between the actual value and the forecasting values.

TABLE 6: Error comparison of China's energy demand prediction.

Index	MSE	MAPE	R <sup>2</sup>
GM (1,1)	10.6261%	28.626	95.4154
MLR	3.3296%	7.748	99.6373
LSSVR	2.3188%	6.537	99.9717
PSO-LSSVR	1.3265%	5.0618	99.9907

TABLE 7: Factors' average growth rate of China's energy demand in 2020-2025 (unit: %).

	Scenario A	Scenario B	Scenario C
GDP	5.6	5.8	6
POP	0.36	0.46	0.58
CCR	-2.3	-2.5	-2.7
RCL	9.3	9.8	10.3

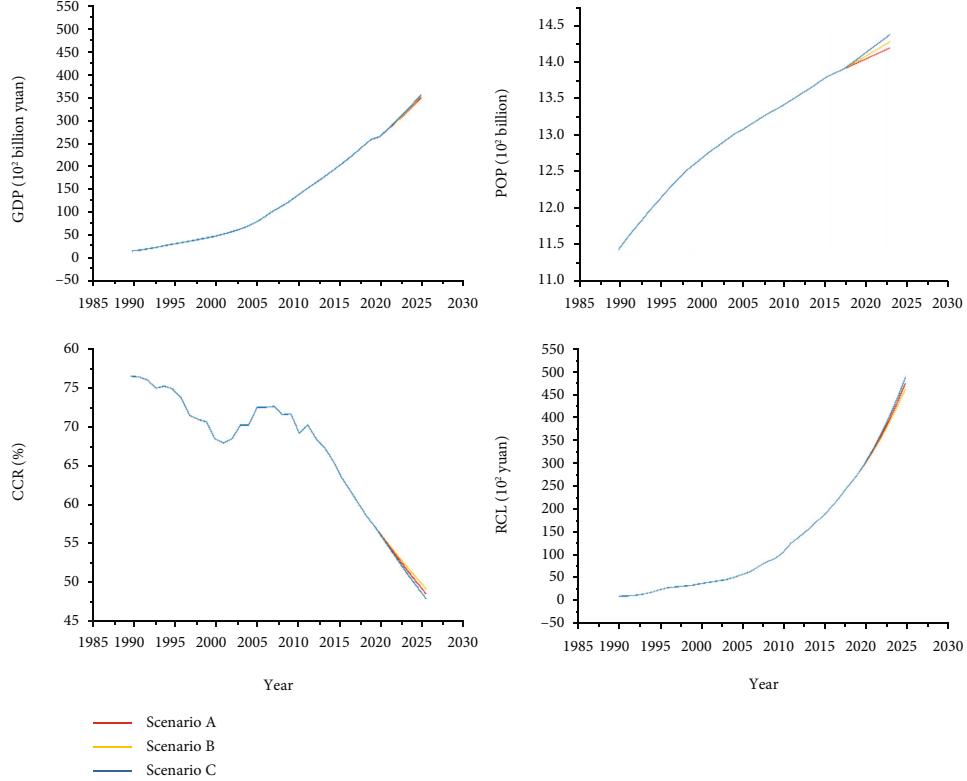


FIGURE 6: Trends of factors affecting energy demand in different scenarios.

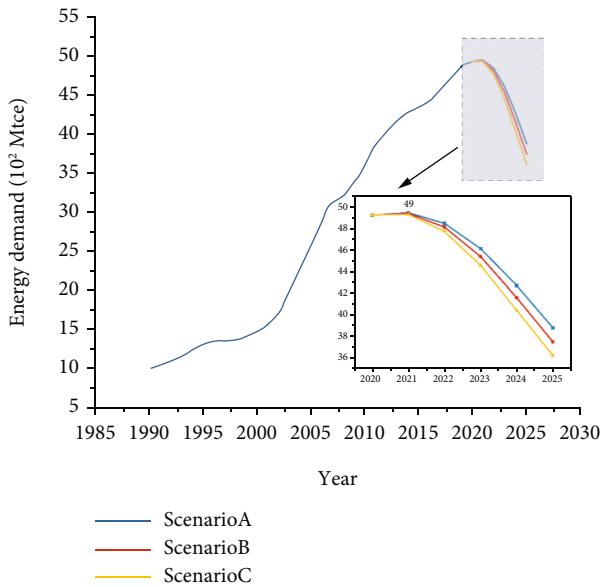


FIGURE 7: Prediction of China's energy demand in different scenarios.

decreased, and the population growth rate reduced to about 0.35 between 2018 and 2019. According to the theory of population transformation, the natural population growth rate decreased gradually. Integrating these trends, the population growth rate in 2020-2025 is 0.36% in scenario A, 0.46% in scenario B, and 0.56% in scenario C, respectively.

The coal consumption ratio in primary energy. With the transformation of the coal industry, technological progress, and the transformation of production and lifestyle, the ratio of coal consumption in primary energy is also declining. In addition, the energy system is being transformed and upgraded from a coal-based energy structure to a renewable-energy-based energy structure. “The Guiding Opinions on Energy Work in 2021” requires that the ratio of coal consumption in primary energy should be reduced to less than 56% in 2021 [32], and “China Energy Development Report” points out that by the end of the 14th five-year plan, the ratio of coal consumption in primary energy is expected to drop to about 51% by 2025 [33]. Consequently, the decline rate of the coal consumption ratio in 2020-2025 is -2.3% in scenario A, -2.5% in scenario B, and -2.7% in scenario C, respectively.

**5.1.3. Residential Consumption Level.** At the 19th National Congress of the Communist Party of China, it is put forward that people’s living is better off, and the proportion of middle-income groups increases remarkably by 2030. Since our country adopted the reform and opening-up policy, economic development has progressed significantly, and people already had a comparatively well-off life. The growth of residential consumption level has been relatively stable at 9.8% over the past eight years. At the same time, China’s economy began to change its mode from high-speed development to medium-high speed development. The residential consumption level will maintain stable growth for a long time. Given the above, during 2020-2025, the growth rate of real RCL

will be 9.3% in scenario A, 9.8% in scenario B, and 10.3% in scenario C, respectively.

As described above, the central assumptions of the factors influencing energy demand in different scenarios are listed in Table 7.

**5.2. Forecasting Results.** This section implements the PSO-LSSVR model to forecast China's energy demand in 2020-2025 using Matlab2012a programing language.

In different scenarios, the possible trends of factors influencing energy demand are listed in Figure 6. As of 2025, the coal consumption ratio was already less than 50%, which means that energy structure adjustment has been completed. The residential consumption level improves sharply, which means closer to the second centennial goal.

The estimation results of energy demand in China during 2020-2025 are shown in Figure 7. It can be seen that China's energy demand will peak around 2021 in all three scenarios, which satisfies the goal proposed in "the 13th Five-Year Plan," and the peak is about 4.9 billion tce. By 2025, China's energy demand will decrease to around 4.39 billion tce, 3.99 billion tce, and 3.91 billion tce in scenarios A, B, and C, respectively. According to the forecasting results, energy conservation policy will achieve the desired effects. If we continue to implement the active energy transformation policy and energy conservation policy, the total energy demand may continue to decline in a short time.

China's economy has begun to enter a new normal. The industrial structure has entered the stage of profound adjustment. The industrialization process has entered the late phase, and the residential consumption level has increased. These indicate that energy demand in China will enter a saturated period, and the peak of total energy consumption is about to arrive.

## 6. Conclusions and Policy Recommendations

In this paper, the hybrid model, the LSSVR model optimized by the PSO algorithm, is proposed to forecasting China's energy demand during 2020-2025. It outperforms other forecasting modes significantly, especially the energy demand forecasting models. The main conclusions of this paper are summarized as follows:

- (1) The Cointegration and Granger Causality test are effective methods to find the connections between influencing factors and energy demand in China. It indicates that there is significant two-way Granger Causality between GDP, POP, RCL, and energy demand and one-way Granger Causality between POP and energy demand
- (2) The LSSVR model has advantages over other models in dealing with complexity, nonlinearity, and small samples of energy systems. At the same time, based on the comparison results of MAPE, RMSE, and  $R^2$ , the hybrid PSO-LSSVR prediction model is demonstrated to be more accurate than a single model

- (3) According to the prediction of this study, the energy demand of China will peak at 4.9 billion tce in 2022

This paper gives related suggestions on energy development to achieve sustainable economic growth based on energy demand analysis and forecasted results:

- (1) Insist on saving energy and reducing consumption. Active population policy will lead to more energy demand, which is contrary to saving energy, reducing consumption, and sustainable development
- (2) Accelerate energy structure adjustment and develop renewable energy. Different types of energy have different efficiency. Developing efficient energy is an effective way to save energy and reduce consumption. Therefore, it should speed up the adjustment of energy structure and increase the proportion of clean energy, such as hydropower, wind power, and nuclear power
- (3) Adjust the economic structure. By adjusting the economic structure, the demand for high-energy and low-efficiency products is shifted to low-energy and high-efficiency ones, increasing economic efficiency and reducing energy demand

In this article, the PSO algorithm is used to search the optimal parameters of the SVM model. Based on this, other heuristic algorithms can be used for parameter optimization, such as the sparrow search algorithm and whale optimization algorithm.

In future studies, metering algorithms can be used to find the main factors affecting energy consumption. Also, the innovative hybrid prediction algorithm can be used to forecast different energy types such as natural gas, wind energy, and solar energy.

## Data Availability

No data were used to support this study.

## Conflicts of Interest

The authors declare no conflict of interest.

## Authors' Contributions

In this work, each author has his own full-time responsibility. More in detail: J.Z. Wang has written Section 1; Y. F. Yang has realized Sections 2, 3, 4, and 5; Y. R. Wang has dealt with Section 6. L. Han has mapped figures in this paper with origin2021b.

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