PV Power Prediction Based on ABC-FCM Optimized SVM

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Abstract. The safe operation of photovoltaic (PV) grid-connected requires high accuracy of PV power prediction. Although support vector machine (SVM) has advantages in solving the non-linearity of prediction data, it has many problems, such as slow convergence, easy to fall into local optimal solution, dimension disaster, and the selection of penalty factor $c$ and kernel function width $\sigma$, which have a deep impact on prediction accuracy. In this paper, the artificial bee colony (ABC) algorithm combined with fuzzy C-means clustering (FCM) algorithm is proposed to optimize SVM for PV power forecasting. FCM is used to calculate the value of the fuzzy membership degree to mark the normality of the samples to generate the fuzzy samples, Optimizing the selection process of SVM parameters using ABC algorithm. The fuzzy samples are input into SVM optimized by ABC algorithm for training, and finally used for PV power prediction. The experimental results show that the resolvable coefficient is close to 1, the root mean square error and relative error of the predicted results decrease, the prediction accuracy of ABC-FCM SVM has been improved, where can be seen through predicted curve and the optimization ability and fitting ability have also been enhanced. It can provide some scientific reference for the development of PV power prediction technology.

1. Introduction
On December 29, 2016, the National Development and Reform Commission and the National Energy Administration of China issued a notice on the “Revolutionary Strategy for Energy Production and Consumption (2016-2030)”[1]. It is pointed out that China's energy future development situation is to adhere to the concept of "green water and green mountains are Jinshan and Yinzhan" and develop towards green and low-carbon direction. To build an energy-conserving consumer society, it is required that by 2020, clean energy will become the main part of energy increase, accounting for 15%; by 2030, the proportion will reach to 20%, and strive to account for more than 50% by 2050[2]. As solar energy has less pollution and wide range of sources, it has received more attention in application. However, due to meteorological factors, solar power generation is intermittent, random and unstable[3]. With the increasing capacity of PV integrated into power grid, the coordination between conventional power supply and PV power generation is becoming increasingly prominent[4]. Predicting PV power in advance and accurately can effectively reduce the impact of PV grid-connected on power system, help the power dispatching department to plan, dispatch and control the operation mode of power grid reasonably, and improve the power quality of power grid and PV energy consumption capacity.

At present, the methods of power forecasting for volt generation are mainly divided into mathematical statistics method and artificial intelligence method. Statistical methods include grey theory prediction method, multiple linear regression method and time series prediction method, such as autoregressive integral moving average model (ARIMA), Markov chain[5]. Artificial Intelligence Method mainly includes BP neural network[6] and SVM and it's derivation or fusion technology[7]. In many prediction methods, SVM is widely used, especially in solving non-linear problems. But it is
usually used to optimize parameters by grid search cross-over method. This optimization method not only wastes resources but also consumes more time, and converges slowly in the later stage of high-dimensional samples and is easy to fall into local optimum solution.

Aiming at these shortcomings, this paper proposes an ABC algorithm combined with fuzzy C-means clustering algorithm to optimize the SVM for PV power generation prediction algorithm. It uses the unique labor division and collaborative search strategy to optimize the SVM penalty factor $c$ and kernel parameter $\sigma^{[9]}$. The illumination intensity, temperature, humidity and wind speed are selected as the eigenvalues of the sample, and the fuzzy membership degree is calculated by the C-means clustering method to mark the normality of the sample to generate the fuzzy sample. Then 1650 fuzzy samples are input into the SVM optimized by the ABC algorithm for training, and then 100 samples are randomly selected for verification to verify the effectiveness of the improved algorithm.

2. Artificial Bee Colony Algorithm

The Artificial Bee Colony Algorithm (ABC) was proposed by the Karaboga Group of the University of Ergiyes in Turkey in 2005, which was inspired by the honey collecting behavior of bee colonies in nature$^{[10]}$. The ABC algorithm classifies artificial bee colonies into three categories according to the honey collecting mechanism: hiring bees, observing bees and scout bees, each hiring bee corresponds to a honey source, and the number of hiring bees or observing bees is the number of honey sources$^{[11]}$. Bees carry out different nectar activities according to their respective divisions of labor, and realize the sharing and exchange of nectar source information to find the best source of honey. When the algorithm is used to optimize the parameters, the amount of nectar contained in the honey source corresponds to the fitness value of the parameter, and the process in which the bee searches for the best honey source is the process of searching for the optimal parameters.

The main iterative processes of ABC algorithm implementation are as follows:

**Initialization phase:** Each honey source constitutes a multidimensional parameter vector, then the scattered population data is initialized, and the initialized solution will be randomly generated by the equation of equation (1)$^{[12]}$.

$$x_{ij} = x_{j\text{min}} + \text{rand}(0,1)(x_{j\text{max}} - x_{j\text{min}})$$

(1)

Where $x_{ij}$ is the $j$-th dimensional vector of the $i$-th bee, where $i \in [1, SN], j \in [1, D], SN$ is the number of honey sources, $D$ is the vector dimension; $\text{rand}(0, 1)$ represents the interval of random normalization; $x_{j\text{min}}$ and $x_{j\text{max}}$ represent the lower and upper limits of the search range, respectively.

**Hiring bee stage:** Each hiring bee corresponds to a single honey source $x_i$, and the hiring bee searches for a new honey source $v_i$ by searching the neighborhood of the honey source $x_i$, and then replaces $x_i$ with $v_i$, $v_i$ is defined by equation (2) as follows:

$$v_{ij} = x_{ij} + \phi_{ij} (x_{ij} - x_{ij})$$

(2)

Where $v_{ij}$ represents the $j$-th element of $v_i$, $x_{ij}$ represents the $j$-th element of $x_i$, $\phi_{ij}$ is a random number between $[-1, 1]$. Hire bees by comparing the honey source $x_i$ and $v_i$, the best choice. After that, the hiring bees return to the hive and share the new best honey source information to the observation bee through the form of a swing dance.

**Observing bee stage:** Observing bees evaluate the honey source information shared by all the hiring bees and selecting a honey source proportional to the amount of nectar. $P_i$ is to be indicated the probability of observing bees choosing to employ bees to share information about honey sources, then the expression is as follows$^{[13]}$:

$$P_i = \frac{\text{fit}_i}{\sum_{j=1}^{SN} \text{fit}_j}$$

(3)
Where, \( f_{it} \) and \( f_i \) represent the fitness and objective function of the honey source \( i \) respectively. Therefore, it is more likely to choose a better honey source during the observing bees stage. Once the observing bees have selected a honey source, a new honey source \( v_i \) will be generated by equation (2). then repeat the hiring bees phase, keeping the best nectar in \( x_i \) and \( v_i \) according to the greedy selection strategy.

It can be seen from the above process that the updated search equations of the employment bee and the observation bee stage are basically the same, and the different places mainly employ the bee stage search process to traverse each honey source, and the observation bee stage only has the opportunity to select the honey source according to the probability value \( p_i \) updated.

**Scouting bee stage:** When a honey source is not improved after the hiring bee has tried to update the search exceed preset limit, the honey source will be abandoned by the associated hiring bee, and the hiring bee will become a scout bee. Then replace the abandoned source with a new source of honey randomly found by the scout bee.\(^{[14]}\)

The process of ABC algorithm optimization is shown in Figure 1. The optimal honey source of the result output corresponds to the optimal parameter.

![Figure 1. Iterative process of ABC](image)

### 3. Fuzzy theory optimization support vector machine

Fuzzy theory optimization SVM, Which the fuzzy membership degree \( \mu \) is introduced to mark the normality of the sample, and generating fuzzy samples\(^{[15]}\). The fuzzy C-means clustering method is used to calculate the value of fuzzy membership.

When FCM calculates \( \mu_i \), the categories are divided according to the similarity of the samples, assuming that the set of training samples given in advance is:

\[
\{x_i, y_i \}, i = 1, 2, \ldots, N
\]

The cluster loss function defined by the membership degree is as shown in equation (6):

\[
J_f = \sum_{j=1}^{C} \sum_{i=1}^{N} \left( \mu_j(x_i) \right)^b \left\| x_i - m_j \right\|^2
\]

(6)

Where \( N \) is the number of samples, \( C \) is the number of categories of classification; \( i \) is the sample number; \( j \) is the cluster number; \( \mu_j(x_i) \) is the membership function of the \( j \)-th class of the \( i \)-th sample; \( b \)
is the degree of blurring of the clustering result. The constant, whose value is greater than 1; \( m_j \) is the cluster center of the \( j \)-th class.

The limit of \( m_j \) is calculated by formula (6) and the iteration formula of clustering center is obtained as formula (7):

\[
m_j = \frac{\sum_{i=1}^{N} [\mu_j(x_i)]^p x_i}{\sum_{i=1}^{N} [\mu_j(x_i)]^p}
\]

\[j = 1, 2...C \]  \hspace{1cm} (7)

The limit of \( \mu_j(x_i) \) is calculated by formula (6), and the iteration formula of membership degree is obtained as formula (8):

\[
\mu_j(x_i) = \frac{\left( \frac{1}{\sum_{j=1}^{C} \sum_{i=1}^{N} 1 \left\| x_i - m_j \right\|^p} \right)^{\frac{1}{p-1}}}{N}
\]

\[i = 1, 2...N, \ j = 1, 2...C \]  \hspace{1cm} (8)

FCM algorithm determines the value of the membership degree by the proportion of the contribution of the training sample in the class. The linear function of the distance from the sample to the center of the class is the membership function. The position of the cluster center should be pre-estimated, and then the deviation between the cluster center and the actual cluster center should be corrected repeatedly to adjust to the minimum of the distance between each data point and the cluster center. The specific iterative process of the algorithm is shown in Figure 2:

**Figure 2. Flow chart of FCM algorithm**
The membership value obtained by FCM algorithm is introduced into support vector machine to make the sample with fuzzy membership, then the sample set is as follows:

$$\{ (x_i, y_i, \mu_i), i \in 1, 2, ..., n, x_i \in \mathbb{R}_n, y_i \in \mathbb{R} \}$$

(9)

$$n$$ is the number of samples, $$x_i$$ is the input value of the first sample, $$y_i$$ is the output value of the second sample, and $$\mu_i$$ is the relaxation factor of the first sample, $$i = 1, 2, ..., N$$. The optimization formulas are as follows:

$$\begin{align*}
\text{min} & \left[ \frac{1}{2} \|w\|^2 + c \sum_{i=1}^{n} \mu_i (s_i + s_i^*) \right] \\
\text{st.} & \quad y_i - w \cdot \varphi(x) - b \leq \varepsilon \\
& \quad w \cdot \varphi(x) + b - y_i^* \leq \varepsilon \\
& \quad s_i, s_i^* \geq 0, i = 1, 2, ..., n
\end{align*}$$

(10)

Formula (10) is converted into dual form by lagnrange function:

$$\begin{align*}
\text{max} & \quad J = -\varepsilon \sum_{i=1}^{n} \left( \alpha_i + \alpha_i^* \right) + \sum_{i=1}^{n} y_i \left( \alpha_i - \alpha_i^* \right) - \\
& \quad \frac{1}{2} \sum_{i, j=1}^{n} \left( \alpha_i - \alpha_i^* \right) \left( \alpha_j - \alpha_j^* \right) \varphi(x_i) \varphi(x_j) \\
\text{st.} & \quad \sum_{i=1}^{n} \left( \alpha_i + \alpha_i^* \right) = 0 \\
& \quad 0 \leq \alpha_i, \alpha_i^* \leq c \mu_i, i = 1, 2, ..., n
\end{align*}$$

(11)

In the formula, $$\alpha_i$$ and $$\alpha_i^*$$ are Lagrange multipliers, and the upper bound of $$\alpha_i^*$$ is the product of penalty factor and fuzzy membership value, while a sample has only one penalty factor, so the value of fuzzy membership is the main parameter affecting $$\alpha_i^*$$ and determines the prediction accuracy of support vector machine\cite{16}. The decision function of Formula (11) can be obtained by finding partial derivatives of Lagrangian functions as follows:

$$f(x) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) K(x_i, x) + b$$

(12)

4. ABC-FCM Optimized Support Vector Machine for PV Power Prediction

4.1. Sample Selection

In this paper, the PV power and its corresponding meteorological factors are used as the original data. In order to avoid data loss or confusion caused by the system’s own defects or external factors, the collected PV power and meteorological factors data should be checked one by one, and the bad data should be rejected or replaced, so as not to affect the prediction results. After screening, the paper uses 1650 PV power data collected every 10 minutes between 8:00 am and 17:00 pm daily in the december 2014 PV laboratory of Guilin University of Technology as a sample, and the data includes irradiation. Four characteristic values of degree, temperature, humidity and wind speed.

4.2. Data preprocessing

In order to eliminate the computational saturation caused by the different features and dimensions of the original data, this paper uses the normalization equation (13) to process the data to ensure that the
output value of the model with higher accuracy is obtained, and then uses the inverse normalization equation (14) to normalize the output result of the model.

\[ y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \]  
\[ x_i = y_i (x_{max} - x_{min}) + x_{min} \]

In the formula, \( x_i \) denotes the data before normalization, \( y_i \) denotes the normalized data, and \( x_{max} \) and \( x_{min} \) denote the maximum and minimum values of the original data, respectively.

4.3. Kernel function selection

Gauss (RBF) kernel function is selected as the kernel function of support vector machine.

\[ K (x_i, x_j) = \exp \left( -\frac{\|x_i - x_j\|^2}{2\sigma^2} \right) \]  

Where \( \sigma \) is the height-width parameter of the kernel function. In order to improve the performance of the support vector machine model, the ABC algorithm is used to find the optimal penalty factor \( c \) and the kernel function height and width parameter \( \sigma \). The FCM algorithm blurs the sample.

The ABC algorithm is used to find the optimal penalty factor \( c \) and the kernel function height and width parameter \( \sigma \) in this paper. The FCM algorithm blurs the sample, and the ABC combined with the FCM optimization support vector machine predicts the PV power generation process as figure 3 shows:

![ABC-FCM Optimized SVM Flow Chart](image)

4.4. Evaluation indicators

In this paper, the root mean square error value (RMSE) and the coefficient of determination (\( R^2 \)) are used to evaluate the prediction results. The RMSE is used to evaluate the deviation of the measured data from the true value. The smaller the RMSE, the higher the measurement accuracy. Measure the degree of prediction model fitting. The closer \( R^2 \) is to 1, the better the goodness of fit. Conversely, the smaller \( R^2 \) is, the worse the fitting superiority is. The formula is as follows:\(^{[17]}\):

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{pi} - y_{pi})^2}{n}} \]  

(16)
\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{ri} - y_{pi})^2}{\sum_{i=1}^{n} (y_{ri} - y)^2}
\]

(17)

In the above formula, \(n\) is the number of PV power samples tested; \(y_{ri}\) is the true value of the \(i\)-th sample of PV power; \(y\) is the average, \(y_{pi}\) is the predicted value of the \(i\)-th sample; \(i = 1, 2..., n\).

5. Experimental simulation analysis

In order to verify the effect of algorithm optimization, a prediction model of ABC-FCM SVM is established, which the number of ABC algorithm is set to 10 and the number of iterations is set to 20, and \(\text{limit}=10\). The FCM algorithm is used to fuzzify 1650 samples, then the fuzzy samples are input into the ABC-SVM model for training, and 100 samples are randomly selected for prediction test. In order to evaluate the algorithm better, the algorithm is compared with a traditional SVM, a separate ABC-optimized SVM (ABC-SVM), and a separate FCM-optimized SVM (FSVM). The comparison between the algorithm prediction results and relative error results are shown in Figure 4 and Figure 5 respectively. The comprehensive evaluation indicators of each algorithm are shown in Table 1.

![Figure 4. Comparing the predicted results with the actual value](image1)

![Figure 5. Relative Error of Prediction Result](image2)
| Sample Number   | $R^2$  | RMSE |
|-----------------|--------|------|
| SVM             | 0.88   | 311.83 |
| ABC-SVM         | 0.94   | 231.92 |
| FSVM            | 0.92   | 39.14  |
| ABC-FCM SVM     | 0.96   | 20.04  |

It can be seen from the prediction results in Figure 4 that the results of the SVM algorithm and the ABC-SVM algorithm are significantly different from the actual values, that is, the prediction accuracy is poor; the SVM algorithm is closer to the actual value after the FCM optimization; but the ABC combination The FCM algorithm optimizes the SVM algorithm and the prediction result curve is closer to the actual value curve than the other three algorithms. From the prediction result relative error curve of Figure 5, it can be seen that the relative error curve fluctuation degree of SVM, ABC-SVM, FSVM and ABC-FCM optimized ABC algorithm is successively decreased; the comprehensive evaluation index of Table 1 shows that after ABC-FCM optimization, the SVM algorithm has a smaller root mean square error and a coefficient of resolution of 0.96, which is closest to 1. The above analysis results show that the ABC-FCM optimized ABC algorithm not only improves the accuracy of PV prediction results, but also enhances the optimization ability and fitting ability.

6. Conclusion
In this paper, the artificial bee colony algorithm is combined with the C-means clustering algorithm in fuzzy theory to optimize the support vector machine and used for PV power generation prediction. Firstly, the four meteorological factors of solar irradiance, ambient temperature, ambient humidity and wind speed are selected as sample eigenvalues, and the fuzzy membership degree obtained by FCM is used to blur the sample. Secondly, the ABC algorithm is used to optimize the penalty factor $c$ and kernel function of SVM. The high width $\sigma$ enhances the optimization function of the SVM; finally, the fuzzy samples are input into the ABC-SVM model for training. After analyzing the experimental prediction results, the SVM prediction model optimized by ABC and FCM improves the prediction accuracy, shortens the time of optimization parameters of the algorithm, and has a good fitting effect, which can be applied to the field of PV power generation prediction.

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