IGBT junction temperature prediction method based on improved artificial bee colony algorithm for optimizing SVR

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Abstract. Aiming at the low precision of IGBT thermal parameter junction temperature prediction method and the need to extract multiple parameters and being vulnerable to load, the improved artificial bee colony algorithm optimized support vector regression machine (ABC-SVR) is used to predict the IGBT junction temperature. Firstly, the formula for updating the honey source in the artificial bee colony algorithm (ABC) is improved, and the fitness probability of Follower bee select honey source is introduced to construct the weight function; Then the problem of support vector regression (SVR) parameter selection is transformed into the parameter combination optimization problem, then establish an optimal SVR model; Finally, the data from the IGBT accelerated aging test provided by the National Aeronautics and Space Administration (NASA) is taken as a sample, the predicted results of the improved ABC-SVR model and the common ABC-SVR model were compared and analyzed. Through the simulation results, the prediction effect of improved ABC-SVR model is better than the common model, and the running time is greatly reduced, it has greater precision in junction temperature prediction.

1. Introduction
Insulated gate bipolar transistor (IGBT) is a power semiconductor device which is widely used in power generation and distribution, aerospace, communications, and new energy systems in recent years. As its power level become higher and the working environment becomes worse and worse, the stricter requirements for the reliability of IGBT are put forward. As an important parameter of IGBT reliability, the operating junction temperature has an important impact on the performance of devices: excessive junction temperature can cause semiconductor devices to fail. According to statistics, about 60% of device failures are caused by excessive temperature, and the device failure rate is doubled for every 10°C rise in temperature[1]. Due to the package characteristics and working environment of the IGBT module, the junction temperature is not easy to obtain. At present, the main methods of obtaining junction temperature are mainly divided into two categories: simulation method and detection method. The simulation method used in [11] is complex in modeling, long in calculation time, large in error, and cannot be used for real-time detection of IGBT junction temperature. The physical contact method and infrared thermal imaging method in the detection method need to open the device package and cannot be used in engineering practice. The thermal parameter method adopted in [12] has low precision, needs to extract multiple parameters and is susceptible to load. In summary, the junction temperature of IGBT is still difficult to obtain, and the above problem can be better solved by machine learning algorithm.

Support vector machine (SVM) is a learning algorithm developed in the 1990s, which can solve small samples, nonlinear, over-learning and local minimum points, it has been widely recognized in the world, and has been well applied in the fields of text classification, image classification, bioinformatics and
function fitting. However, it is very difficult to select the appropriate SVM parameters. Therefore, the SVM parameter determination problem can be transformed into a combinatorial optimization problem through an intelligent algorithm.

The Artificial Bee Colony Algorithm (ABCA) is a stochastic population random optimization algorithm proposed in 2005, which mimics the behavior of bee collecting honey. The advantage of this algorithm is that there are few parameters, global search and local search are performed in each iteration, so the probability of finding the optimal solution is greatly increased. However, the artificial bee colony algorithm still has shortcomings such as low search accuracy, long search time, and easy to fall into local optimal solutions.

2. Support vector regression machine

The support vector regression machine is obtained by generalizing the SVM from the classification problem to the regression problem. At this time, the SVM algorithm is also called Support Vector Classification (SVC) [4].

Provided the known training set \( Y = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), ..., (x_n, y_n)\} \), the regression model is:

\[
 f(x) = w^T \Phi(x) + b
\]  

(2.1)

Where \( \Phi(x) \) is the nonlinear mapping of input space \( X \) to high dimensional space, \( w \) is the weight vector, and \( b \) is the bias. Introducing two relaxation variables \( \xi, \xi^* \) and estimating the model as:

\[
 \begin{align*}
 R(f) &= \min \left( \frac{1}{2} \|w\|^2 + C \frac{1}{n} \sum_{i=1}^{n} (\xi_i + \xi_i^*) \right) \\
 \text{s.t.} \quad &y_i - w^T \Phi(x_i) - b \leq \xi_i + \xi_i^* \\
 &w^T \Phi(x_i) - b - y_i \leq \xi_i + \xi_i^* \\
 &\xi_i, \xi_i^* \geq 0(i = 1, 2, ..., n)
\end{align*}
\]  

(2.2)

By introducing Lagrangian multipliers \( (\alpha, \alpha^*, \mu, \mu^*) \), the dual problem can be obtained as:

\[
 \max \sum_{i=1}^{n} [y_i (\alpha_i^* - \alpha_i) - \epsilon (\alpha_i^* + \alpha_i)] - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} [(\alpha_i^* - \alpha_i) x_i^T x_j (\alpha_j^* - \alpha_j)]
\]  

(2.3)

s.t. \( \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) = 0, 0 \leq \alpha_i, \alpha_i^* \leq C \)

The decision function of the support vector machine is:

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

(2.4)

Where \( K(x_i, x) \) is the kernel function, this paper selects the Gaussian kernel function, and its formula is:

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

(2.5)

3. Artificial Bee Colony Algorithm and its improvement

3.1 Artificial Bee Colony Algorithm

The main idea of the Artificial Bee Colony Algorithm is to imitate the bee colony. The bees in the swarm can be divided into employed bees (also known as Leader) and unemployed bees (including Scouter and Follower) according to their different tasks. The employed bee stores information about the honey source and shares it with certain probabilities to other bees; The Scouter bee is responsible for searching for new honey sources; The Follower bee find the source of honey through the information shared with the employed bee. Each employed bee corresponds to a honey source and searches for the neighborhood of the honey source in iterations, and according to the richness of the honey source (fitness) hire Followers
to search for new honey sources. If the honey source does not improve after repeated iterations, the honey source is abandoned, the employed bee is turned into a Scouter, and the new honey source is randomly searched.

Provided that the number of parameters that need to be optimized by the ABC algorithm is $D$, then randomly generate $SN$ $D$-dimensional solution vectors during initialization:

$$x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$$

$i \in \{1, 2, \ldots, SN\}$

Where $SN$ is the number of honey sources, and the formula for randomly generating solutions is:

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

$j \in \{1, 2, \ldots, D\}$

(3.1)

The employed bee records its current optimal value and searches in the current honey source neighborhood. The search formula is:

$$v_{ij} = x_{ij} + \text{rand}(-1,1)(x_{ij} - x_{kj})$$

$k \in \{1, 2, \ldots, SN\}$

(3.2)

Where $k$ is randomly generated and $k \neq i$.

The Follower bee is hired by employed bee according to the probability $P_i$, the formula of $P_i$ is

$$P_i = \frac{\text{fit}_i}{\sum_{n=1}^{SN} \text{fit}_n}$$

(3.3)

Where, $\text{fit}_i$ represents the fitness of the $i$-th solution vector, i.e. the richness of the $i$-th honey source. Obviously, the greater the richness of the honey source, the greater the probability of being selected.

In order to prevent falling into local optimum, the ABC algorithm sets a parameter $\text{limit}$, when a honey source iteration $\text{limit}$ is not improved, the honey source will be abandoned, and the hired bee randomly generates a new honey source according to formula (3.1) instead of this honey source.

3.2 Improvement of artificial bee colony algorithm

The formula for the honey source search in the basic ABC algorithm is (3.2), the global search ability is poor, the convergence speed is slow, and the search for a single hired bee is completely random and does not communicate with other bees. Therefore, it is easy to fall into local optimum, and the probability of successful update optimization is lower. In order to overcome the above shortcomings, based on the formula (3.2), introducing the fitness probability $P_i$ in the formula (3.3) to construct the weight function, make formula (3.2) into the following form:

$$v_{ij} = x_{ij} + \text{rand}(-1,1)\phi_i(x_{ij} - x_{kj})$$

$$\phi_i = 1 - P_i$$

(3.4)

By introducing the weight function in formula (3.4), the size of the search neighborhood can be adaptively adjusted. Since the $P_i$ contains the fitness of all solutions, the weight function introduced in the above form can exchange information between the current solution and other solutions, and it is conducive to finding the optimal solution vector more accurately.

As the $\text{fit}_i$ increases, the weight function is decremented. When the fitness of the new solution is larger than the old solution, i.e., $\text{fit}(v_{ij})$ is greater than $\text{fit}(x_{ij})$, $P(v_{ij})$ is greater than $P(x_{ij})$, it is proved that the solution is successfully optimized. At this time, the weight function $\phi(v_{ij}) = 1 - P(v_{ij})$ is less than $\phi(x_{ij}) = 1 - P(x_{ij})$, which plays the role of narrowing the neighborhood, so as to avoid missing the region of the optimal solution and improve the search efficiency and convergence speed. Conversely, if $\text{fit}(v_{ij})$ is less than $\text{fit}(x_{ij})$, the new solution is not optimized (even worse than the previous solution), at this time, the weight function $\phi_i$ is increased, and the search neighborhood is expanded accordingly, which is beneficial to strengthen global search, promote information exchange, and improve search accuracy.
4. SVR parameter optimization model and steps

4.1 SVR parameter optimization model

The SVR kernel function and its parameter determination are the key points in establishing the SVR model, which can greatly reduce the amount of calculation and avoid the "dimensional disaster". This paper chooses the Gaussian kernel function (also called radial basis kernel function, RBF, as in equation (2.5)). There are three main parameters that need to be optimized by the artificial bee colony algorithm: kernel function width $\sigma$, insensitive loss function $\varepsilon$ and penalty factor $C$.

The kernel function width $\sigma$ represents the radial range of the function, reflecting the degree of correlation between the support vectors. If $\sigma$ is too small, the connection between support vectors is slack, the learning machine is relatively complex, the promotion ability is not strong. And if $\sigma$ is too large, the influence between support vectors is too strong, the regression model is difficult to achieve sufficient accuracy. The insensitive loss function $\varepsilon$ controls the width of the regression function's insensitive region to the sample value, affecting the number of support vectors. If the value of $\varepsilon$ is too small, the regression accuracy is high, but the model is complicated and loses the promotion ability. If the value is too large, the model is simple and the learning precision is not enough. The penalty factor $C$ reflects the degree of punishment of the algorithm for sample data beyond the $\varepsilon$ pipeline, and its size affects the complexity and stability of the model. When $C$ is too small, the training error becomes larger, $C$ is too large, the learning accuracy becomes higher, but the model generalization ability also deteriorates.

How to choose the support vector machine parameters is still difficult. At present, there are: Direct determination methods, grid search methods, cross-validation methods and intelligent algorithms. But these methods have certain disadvantages: Direct determination requires a higher prior knowledge; The grid search method has a large amount of calculation and is not accurate; The cross-validation method takes a long time and does not apply to the actual situation. Therefore, using the ABC algorithm to convert the determination of SVR parameters into a combinatorial optimization problem is a very effective solution. This paper optimizes the parameter combination of SVR by establishing the following model:

$$F(\sigma, \varepsilon, C) = \max_{C} \max_{\varepsilon} \max_{\sigma} \text{fit}(SVR(\sigma_i, \varepsilon_i, C_i))$$

subject to:

$$\sigma_i \in [\sigma_{\min}, \sigma_{\max}]$$

$$\varepsilon_i \in [\varepsilon_{\min}, \varepsilon_{\max}]$$

$$C_i \in [C_{\min}, C_{\max}]$$

(4.1)

4.2 Steps to optimize the model

The specific steps for optimizing the parameter combinations in the above model (4.1) are:

Step 1: Set the parameters, including the number of bee colonies $\text{ColonySize}$, maximum search cycles $\text{MaxCycle}$, the range of the insensitive loss function $\varepsilon$: $lb_e$ (lower band of epsilon) and $ub_e$ (upper band of epsilon), the range of the kernel function parameter $\sigma$: $lb_s$ and $ub_s$, and the range of penalize parameter $C$: $lb_C$ and $ub_C$.

Step 2: Define fitness function $\text{fit}$:

$$\text{fit}_i = \frac{1}{f_i + 1}$$

(4.2)

Where $f_i$ is the root mean square error of the SVR predicted value and the actual sample value, and the degree of fitness can directly show the quality of the SVR model;

Step 3: Randomly select two data, use one of the data as training samples, and train the IGBT junction temperature prediction model based on improved artificial bee colony algorithm to optimize the support vector regression machine. Using another data as a test sample to determine the accuracy of the junction temperature output of the IGBT junction temperature prediction model;

Step 4: Initializing the bee colony, each honey source is a parameter combination $(\varepsilon, \sigma, C)$ to be
optimized by the SVR, and randomly takes values according to the value range in the Step 1;

Step 5: Substituting each initial parameter combination into the SVR to calculate the root mean square error between the predicted and actual values, and calculate the fitness of each honey source, compare the fitness of each honey source, and record the current best combination;

Step 6: The ABC algorithm mimics the behavior of collecting honey. The employed bee constantly searches for the honey source, calculates the fitness and compares the honey source with higher fitness. The method of updating the honey source is carried out according to the improved formula (3.4);

Step 7: If the number of searches exceeds limit, the honey source with higher fitness is not found, then the honey source is abandoned, and a new honey source is randomly generated instead of the original honey source according to the improved formula (3.1);

Step 8: Record the current optimal honey source, that is, the optimal parameter combination \((\varepsilon, \sigma, C)\) and the fitness of the combination, and jump to Step 6 until the algorithm runs to the maximum number of iterations MaxCycle, and then the optimal parameter combination is obtained;

5. Model parameter settings and prediction results

5.1 Model parameter settings
In order to better compare the performance of the common ABC-SVR algorithm and the improved ABC-SVR algorithm, the parameters are the same: the number of bee colonies ColonySize is 50, the maximum number of search times limit is 150, the maximum number of iterations MaxCycle is 300, the range of insensitive loss function \(\varepsilon\) is 0.01–0.5, and the range of Gaussian kernel function parameters \(\sigma\) is 0.5–1, the penalty parameter \(C\) ranges from 0.01 to 0.5.

5.2 Forecast results
Sample data from the IGBT accelerated aging test provided by the National Aeronautics and Space Administration (NASA). The data includes the IGBT junction temperature \(T_j\) and the Collector-Emitter voltage \(U_{CE}\) and current \(I_{CE}\) at the current junction temperature. Using \(U_{CE}\) and \(I_{CE}\) as inputs and junction temperature \(T_j\) as output, the data sample set \(Y={(x_1, T_{j1}), (x_2, T_{j2}), (x_3, T_{j3}), ..., (x_n, T_{jn})}\), where \(x_i=(U_{CEi}, I_{CEi})\). The sample was randomly divided into two, one for training the model and the other for testing the accuracy of the model output.

Substituting the data into the common ABC-SVR model and the improved ABC-SVR model, the ABC algorithm optimized SVR parameter combination is shown in the table below:

| model            | \(\varepsilon\) | \(\sigma\) | \(C\)  |
|------------------|------------------|------------|--------|
| common ABC-SVR   | 0.1441           | 0.9285     | 0.2503 |
| improved ABC-SVR | 0.1326           | 0.8865     | 0.2259 |

It can be seen from the above table that the optimal parameter combination after optimization and optimization of the algorithm is not the same. The prediction effect when ColonySize is 50 and 100 are shown in the figures below:
Figure 1. Comparison of common ABC-SVR and improved ABC-SVR when ColonySize is 50.

Figure 2. Comparison of common ABC-SVR and improved ABC-SVR when ColonySize is 100.

As the figure shown, the predictive effect of improved ABC algorithm is better than the normal ABC algorithm.

The comparison of the root mean square error (RMSE), the mean absolute percentage error (MAPE) and the running time of the two methods are shown in the table below (when ColonySize is 100):

| Method              | RMSE  | MAPE  | TIME |
|---------------------|-------|-------|------|
| common ABC-SVR      | 1.8368| 0.5538| 22   |
| improved ABC-SVR    | 1.3254| 0.4745| 13   |

6. Conclusion
The artificial bee colony algorithm is a newly developed intelligent evolutionary algorithm with strong search ability, however, there is a shortcoming of slow convergence and easy to fall into local optimum. Therefore, based on the original algorithm, the update formula of honey source has been improved, the performance of the algorithm is improved to a certain extent, the global search capability is enhanced, and the search neighborhood size can be adaptively adjusted, the convergence speed is accelerated, and the prediction accuracy is improved. The prediction results show that the improved ABC algorithm can solve the problem of parameter combination optimization better than the original algorithm.

The improved artificial bee colony algorithm is used to optimize the support vector machine model to predict the junction temperature of IGBT. Compared with the common ABC-SVR algorithm, the improved ABC algorithm can improve the prediction accuracy and have better generalization ability and
generalization ability. This model can be applied to practical projects where IGBT junction temperature acquisition is difficult.

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