Parameter Identification of Comprehensive Load Modeling Based on Improved Genetic Algorithm

Lai Wei* and Jian Zhang
Industrial Technology Research Institute, Zhengzhou University, Zhengzhou 450001, China

*Corresponding author e-mail: weilai@gs.zzu.edu.cn

Abstract. As the intelligent analysis and calculation of information developing very fast, the algorithms for load model parameter identification are growing fast the same time, these algorithms were aimed at quick convergence, improving calculation accuracy and so on, making the identification for load model parameter being more and more fast and accurate. This paper provides an improved GA with adaptive ability to identify the parameter of comprehensive load modeling. Choosing TVA comprehensive load model as the computational model, and use the improved GA given by this paper to identify the parameter of the model. The computer simulation result shows that the improved GA proposed by this paper has improved the calculation effect, especially has palpable effects on accelerating convergence and shorten the time of identification.

1. Introduction
Electrical load is one of the most important object of study, it plays a definitely important position in the analysis and control of the entire grid. The inaccuracy of the load model or the inaccuracy of the model parameters will directly affect the accuracy and reliability of the theoretical results, making the calculation results too pessimistic or optimistic, and this would lead to unnecessary waste of resources or system operational risks.

How to identify the key parameters of the load model quickly and accurately is one of the core issues of load modeling. Genetic Algorithm has been widely concerned and applied since it been put forward. It is a parallel random search algorithm based on the principle of selection and genetics. It is an optimization method that seeks global optimum and is insensitive to initial values [1]. In document [2], genetic algorithm is applied to parameter identification of load modeling, and a better result is obtained than the traditional optimization method. But studies have shown that traditional genetic algorithms have two major defects: precocious maturity and slow convergence [3-4]. In this paper, an improved algorithm is proposed, which has excellent performance in shortening the time of identification and improving the accuracy of model fitting. It is an excellent algorithm for load modeling.

2. Improvement of genetic algorithm
Genetic algorithm, also known as GA, is a computational model of biological evolution process of natural selection and genetic mechanism simulating Darwin's theory of biological evolution. It's a way to search for optimal solution by simulating natural evolution process. The basic idea is to generate the initial population of gene coding according to certain rules. Then, starting from the initial population of
these potential solutions, we select strong fitness individuals for crossover and mutation to generate populations representing the new solution set, thus every new generation is better than the previous generation. In the end, the optimal individual in the final generation of the population is the approximate optimal solution of the corresponding problem. The calculation process of GA involves the following five main elements: initial population setting, selection strategy, cross strategy, mutation strategy and fitness function selection [3, 4].

2.1. Initial population setting
The population is the root of the genetic algorithm, and it is also the basic condition that the genetic algorithm can search the approximate optimal solution in the global scope. In this paper, the interval of initial population generation is set to the whole feasible domain, and a certain number of individuals are randomly generated in this interval, which constitute "initial random population", called N in this paper. There are certain differences between the individual individuals in the initial population and all over the whole feasible domain.

2.2. Selection and crossover strategy
The traditional selection strategies include preferred choice, roulette, and Boltzmann selection strategy and so on. There are some other improvement strategies, such as elite strategy, stochastic elite strategy and so on.

In this paper, a comprehensive selection strategy is used to determine the number of individuals replicated according to the proportion of the fitness of each individual, so that more adaptive the unit is, more frequencies it get copied. At the same time, considering the diversity of population and avoiding inbreeding, individuals with a lower fitness have a certain probability to be selected. The probability of their selection depends on the fractional part of the number of individuals replicated. The specific operation process is as follows.

(1) Calculate the sum of the fitness of each unit from every generation, marked as S, then we can get the times that each unit should be copied when S divided by each fitness, mared as $NUM_i$.

$$S = \sum_{i=1}^{N} f_i$$

$$NUM_i = \frac{f_iN}{S}$$

In which, $f_i$ stands for the fitness of every unit, N stands for the total number of a population, $NUM_i$ stands for times that each unit should be copied, $i = 1, 2, 3, ..., N$.

(2) Rounding off each $NUM_i$ in step (1).

$$N_i = \text{int}(NUM_i).$$

In which, $N_i$ stands for the times each unit should be copied. Calculate the difference between the sum of all $N_i$ and $NUM_i$, mared as $s$.

$$s = N - \sum_{i=1}^{N} N_i.$$  \hspace{1cm} (3)

Let the difference between each group of $NUM_i$ and $N_i$ be $r_i$.

$$r_i = NUM_i - N_i.$$  \hspace{1cm} (4)

Sort all $r_i$, select the first $s$ larger corresponding units, and increase the number of times they should be copied.

In such an algorithm, the fraction number of individuals with higher fitness is not necessarily large, but the fraction of replication times of individuals is not necessarily small with low fitness. Therefore, individuals with less fitness are equally likely to be selected to enter the next generation, so that the
diversity of the population is guaranteed to some extent. Of course, the possibility for units with lower fitness being selected is relatively low.

Referring to the elitist strategy mentioned in document [5], this algorithm directly selects the individuals with the highest fitness to go directly to the next generation, so as to avoid losing the best individuals.

The cross strategy is to imitate the process of gene recombination in nature, to exchange genes of chromosomes, so that the original excellent genes can be passed to the next generation of individuals, and eventually produce new individuals with more complex gene structure. The reasonable crossover strategy is the fundamental of ensuring the diversity of population. There are mainly four ways to achieve crossover by genetic algorithm: one point crossover method, K point crossover method, K point scrambling crossover method, uniform crossover method, etc [4]. The two point crossover method has a good performance in speed and accuracy, and it can also meet the needs in the retention of paternal information. Therefore, this paper weighs the operation complexity and the cross results in two aspects, using the two point cross method.

2.3. Mutation strategy
The traditional mutation strategy is to take a fixed mutation probability $p_m$, the advantage of this method is simple and easy to implement, but the disadvantage is that it can not reflect the trend of individual change in the population, but also affect the evolutionary performance of the genetic algorithm, which easily leads to premature convergence. The mutation strategy used in this paper is a linear adaptive mutation strategy. It is based on the size of each individual's fitness to determine the mutation probability of the individual itself. Specifically, the probability of mutation for individuals with relatively large fitness is small, and individuals with less fitness are more likely to have a mutation than those with the greatest fitness. When the individual's fitness is ranked in ascending order, the probability of mutation in each individual is as followed,

$$p_m = 0.1 - \frac{0.1i}{N}.$$  \hspace{1cm} (5)

The advantage of this mutation strategy is that it takes into account the fitness of the individual, and it can adapt itself to the trend of evolution independently based on the development of computation. It has a certain flexibility and is relatively simple to implement and has strong applicability.

3. Integrated load model
The integrated load model used in this paper uses the model structure of the third-order induction motor parallel load static characteristics. As shown in Figure.1 below. In which, IM stands for induction motor, ZIP stands for static load.

![Figure 1. Load model of TVA](image-url)
The three order induction motor model is used in the motor model, and combined with the static ZIP model, we have 14 parameters to be identified. The equivalent circuit diagram of the model is shown in Figure 2 below.

![Figure 2. Equivalence structure of composite load model](image)

In which, \( R_s, X_s \) stand for the resistance and leakage reactance of stator windings, \( R_r, X_r \) stand for resistance and leakage reactance of rotor winding, \( X_m \) stands for stator rotor mutual inductance. Induction motors can be described by the following equations.

\[
\begin{align*}
\frac{dE_{id}}{dt} &= -\frac{1}{T_i} [E'_{id} + (X - X')I_d] - (w - 1)E'_{d} \\
\frac{dE_{iq}}{dt} &= -\frac{1}{T_i} [E'_{iq} + (X - X')I_d] - (w - 1)E'_{q} \\
\frac{dw}{dt} &= -\frac{1}{2H} [T_m - (E'_{d}I_d + E'_{q}I_q)] \\
\end{align*}
\]  

(6)

ZIP static load can be described by the following equations.

\[
\begin{align*}
P_S &= P_Z \left(\frac{U}{U_0}\right)^2 + P_1 \left(\frac{U}{U_p}\right) + P_p \\
Q_S &= Q_Z \left(\frac{U}{U_0}\right)^2 + Q_1 \left(\frac{U}{U_p}\right) + Q_p \\
\end{align*}
\]  

(7)

Besides, the parameters in this model also satisfy the following equations.

\[
\begin{align*}
P_Z + P_1 + P_p &= 1 - K_{pm} \\
Q_Z + Q_1 + Q_p &= 1 - \frac{Q_m}{Q_0} \\
K_{pm} &= \frac{P_{10}}{P_0} \\
M_{1f} &= \frac{S_{mb}/U_0}{S_{mb}/U_b} \\
\end{align*}
\]  

(8)

In which, \( P_0 \) stands for the initial active power of the load measuring point, \( P'_0 \) stands for the initial active power of the equivalent motor, \( S_{mb} \) and \( U_0 \) stands for the rated capacity and voltage of the equivalent motor, \( U_0 \) stands for the initial voltage of the load measuring point, \( E'_q \) stands for the q-axis subtransient potential of the equivalent motor, \( w \) stands for the speed of revolution of the equivalent motor, \( H \) stands for the inertia time constant of the equivalent motor.

4. Using improved genetic algorithm for parameter identification of integrated load model

Assume that the voltage of the integrated load model is \( U \), the parameters to be identified are,

\[
\theta = [R_s, X_s, X_m, R_r, P_p, Q_Z, Q_p, K_{pm}, M_{1f}, H, A, B]
\]
The objective function is defined as follows [6],

\[
W(k) = 0.4 \frac{|\bar{u}(k) - \bar{\bar{u}}|}{\sum_{k=1}^{n}|\bar{u}(k) - \bar{\bar{u}}|} + \frac{0.6}{n} \\
J = \left(\sum_{k=1}^{n} W(k)[\bar{y}(k) - y(k)]^2\right)^{0.5}.
\]  

(9)

In which, \(\bar{y}(k)\) stands for load model’s response at number k sampling point, \(y(k)\) stands for measured load response at number k sampling point, \(W(k)\) stands for the weight of number k sampling point.

The fitness function of the algorithm is defined as follows,

\[
f = \frac{I}{J}.
\]

(10)

The general steps when using this improved genetic algorithm for parameter identification of a comprehensive load model are as follows,

1. Within the given range of \(\theta\), 100 initial individuals are randomly generated as the initial population.
2. According to the method described above, the objective function \(J\) and each individual's fitness function \(f\) can be obtained. And if the fitness of the optimal individual meets the error requirement or the number of iterations reaches the preset maximum number of iterations, the iteration ends.
3. According to the comprehensive selection strategy and individual's fitness, select the good individual to enter the next generation, and the best individual does not participate in the selection and go directly to the next generation.
4. According to the crossover strategy, use the two-point crossing method to cross-pass individuals that were filtered by the previous step.
5. Use a linear adaptive mutation strategy to mutate individuals after the previous step. When this operation is completed, the evolution from the father to the child is completed. The flow of calculation goes to step (2) to continue the cycle.

5. Practical example verification

In order to verify the performance of the improved genetic algorithm used in the parameter identification of the integrated load model, the measured parameters of a substation are used to identify the parameters. The parameters of the measured data were identified using the basic genetic algorithm and the improved genetic algorithm used in this paper. The speed of convergence was measured by the number of iterations and the calculation time. Under the same calculation accuracy, the results of the calculation are shown in Table.1 below.

The parameters showed in the table are all pre-unit values.

From the calculation results in the table, it can be seen that under the same calculation accuracy, the number of iterations used to identify the parameters of the comprehensive load model using the improved genetic algorithm is significantly lower than that of the basic genetic algorithm.

The operating speed of the improved genetic algorithm is also much higher than that of the basic genetic algorithm, and the convergence speed of the calculation results has been significantly improved. It can be concluded that the improved genetic algorithm proposed in this paper is an excellent algorithm for parameter identification of comprehensive load models.
Table 1. Parameter identification comparison result between basic genetic algorithm and improved genetic algorithm

| algorithm | data | \( R_z \) | \( X_z \) | \( X_m \) | \( R_r \) | \( X_r \) | \( H \) | \( K_{pm} \) | \( M_{1f} \) | \( P_P \) | \( P_Z \) | \( Q_P \) | \( Q_Z \) | Number of iterations | Computing time |
|-----------|------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|-------------------|---------------|
| Basic GA  | 1    | 0.2865   | 0.0797   | 2.3503   | 0.0628   | 0.0763   | 0.7533   | 0.5916   | 0.4209   | 0.4064   | 0.6657   | 0.6488   | 0.5379   | 132               | 46"           |
|           | 2    | 0.2924   | 0.1007   | 2.5102   | 0.0981   | 0.0815   | 0.9401   | 0.5742   | 0.3541   | 0.3160   | 0.4807   | 0.5254   | 0.4192   | 133               | 47"           |
| Improved GA | 1   | 0.3338   | 0.1328   | 2.4119   | 0.0666   | 0.0958   | 0.8769   | 0.4932   | 0.4763   | 0.5869   | 0.4358   | 0.1130   | 0.7297   | 17                | 6"            |
|           | 2    | 0.4107   | 0.1952   | 2.5041   | 0.0825   | 0.1107   | 0.9381   | 0.4247   | 0.4108   | 0.4791   | 0.3803   | 0.1018   | 0.6485   | 17                | 6"            |

6. Conclusion

This paper proposes an improved genetic algorithm aiming at the defects of the traditional genetic algorithm itself. The improved algorithm can avoid effectively by reasonably generating random initial populations, selecting optimal individual reservations, and adaptive selection and selection methods. The problems of precocity and inbreeding that are easily caused by traditional genetic strategies. From the results of the last actual calculation, we can see that the improved genetic algorithm proposed in this paper significantly improves the convergence speed of the calculation and shortens the time for identification. In general, the improved genetic algorithm is a more practical and suitable algorithm for parameter identification of power system integrated load model.

References

[1] REN Zi-wu, SAN Ye. Improved Adaptive Genetic Algorithm and its Applocation Research in Parameter Identification [J]. JOURNAL OF SYSTEM SIMULATION, 2006, 18 (1): 41-43.
[2] Ju Ping, Li Defeng. A Study on the Identification Method of the Composite Electric Load Models [J]. Power system automation, 1997 (8): 11-14.
[3] Goldberg D E. Genetic Algorithms in Search, Optimization and Machine Learning [J]. 1989, xiii (7): 2104–2116.
[4] YUN Qingxia. EVOLUTIONARY ALGORITHMS [M]. BeiJing: Metallurgical Industry Press, 2000.
[5] JIN Qun, LI Xinran, LIU Yanyang. An Improved Genetic Algorithm and its Application to Load Modeling [J]. Journal of Power System and Automation, 2006, 18 (2): 35-40.
[6] SHI Jinghai. Load Modeling of Large-scale Power Grid Considering Time-variant Characteristic [D]. North China Electric Power University (BeiJing), 2004.
[7] Jin M, Renmu H, Hill D J. Load modeling by finding support vectors of load data from field measurements [J]. IEEE Transactions on Power Systems, 2006, 21 (2): 726-735.
[8] Renmu H, Jin M, Hill D J. Composite load modeling via measurement approach[J]. IEEE Transactions on Power Systems, 2006, 21 (2): 663-672.