A Research of Icing Forecasting Algorithm Using Genetic Algorithm and Fuzzy Logic

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***Abstract*: According to the icing forecasting problems of transmission line, an icing forecasting fuzzy system was optimized by using genetic algorithm to get a better results. Firstly, a combined fuzzy rules base was established by using a learning algorithm, and combined with the expertise experience fuzzy rules in the field data. Secondly, the parameters of icing forecasting model such as the input-output domain fuzzy division、combined fuzzy rule base and membership function, etc. were optimized by genetic algorithm, moreover, the theory mix of genetic algorithm and fuzzy logic was studied and discussed further. Finally, the monitoring data acquired from transmission line online monitoring system on Guizhou Power Grid of China in 2014 was selected to compare the predicted effects of icing forecasting model before and after optimization.**

Keywords: transmission line; icing; icing forecasting; genetic algorithm; fuzzy logic

INTRODUCTION

Since January 2008, many provinces in southern China suffered a large area, long sleet freezing weather, which leading to a number of transmission line accidents, such as break line, pole collapse, tower collapse, ice flashover and ice-shedding and so on. A large area of the grid in a paralyzed state and the direct economic losses of more than 100 billion yuan. Therefore, it has great engineering practical significance to ensure the safe operation to develop a transmission line online monitoring system, remote real-time monitoring lines icing conditions, establish icing forecasting algorithm which based on monitoring data, and provide ice alarming [1]-[5].

Ice growth prediction model was established previously by the author [6], the dynamic and static performance and control effect of fuzzy system are decided by the fuzzy rules and correct choice of the membership functions. Upon the fuzzy system is established, the fuzzy rules were fixed, the implicit control process does not produce significant changes beyond the control. If the fuzzy rules can't cover all cases, the fuzzy system control effect is likely to be poor. In addition, it is difficult to determine the fuzzy rules on the basis of experience in multidimensional space when the number of input and output variables increase or decrease, and if the number of variables was increase, the number of fuzzy rules to choose space will increase sharply, which is difficult to judge the system control effect [7]-[10]. GA (*genetic algorithm*) is a global search algorithm, according to a set of control effect of fitness function evaluation algorithm, less dependence on the problems, so that can avoid falling into local optimum, and very suitable for optimization design of fuzzy control system [11].

In this paper, firstly a combined fuzzy rules base was established by using a learning algorithm combined with the expertise experience fuzzy rules in the field data. Then GA is used to optimize the parameters of icing forecasting model, such as the input-output domain fuzzy division; combined fuzzy rules base and membership function, etc. Finally, the monitoring data acquired from transmission line online monitoring system on Guizhou Power Grid of China in 2014 was selected to compare the predicted effects of icing forecasting model before and after optimization.

I. COMBINED FUZZY RULES BASE

Assuming the value pairs for the formula (1), x_1 and x_2 are the input, and y is the output. The domain of x_1 and x_2 respectively are: $[x_1^-,x_1^+]$、$[x_2^-,x_2^+]$; the range of y is $[y^-,y^+]$.

Step 1: The fuzzy division for the range of x_1, x_2 and y are used by triangular membership functions. As shown in figure 1 , successively named: Nn, N1, O, P1, Pn. Determining the membership degree of $x_1^{(i)}$、$x_2^{(i)}$、$y^{(i)}$ in the different fields, and assigning the $x_1^{(i)}$、$x_2^{(i)}$、$y^{(i)}$ in a certain field where they have the maximum membership degree.

$$(x_1^{(1)},x_2^{(1)};y^{(1)}),\ (x_1^{(2)},x_2^{(2)};y^{(2)}),\ldots \quad (1)$$

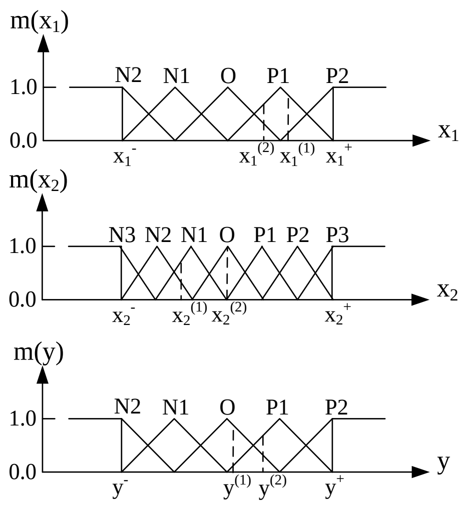

Figure 1: Fuzzy partition of x1、x2、y universe

From the picture 1: for the value pairs of $(x_1^{(1)},x_2^{(1)};y^{(1)})$ and $(x_1^{(2)},x_2^{(2)};y^{(2)})$ are:

$(x_1^{(1)},x_2^{(1)};y^{(1)}) \rightarrow [x_1^{(1)}(0.8$ in P1,max$),x_2^{(1)}(0.7$ in N1,max$);y^{(1)}(0.9$ in O, max$)] \rightarrow$ Rule 1;

$(x_1^{(2)},x_2^{(2)};y^{(2)}) \rightarrow [x_1^{(2)}(0.6$ in P1,max$),x_2^{(2)}(1$ in O, max$);y^{(2)}(0.7$ in P1, max$)] \rightarrow$ Rule 2.

Step 2: Every generated rule was given a strength so that can solve the problems of conflicting among rules. If x_1 is A，x_2 is B，y is C，intension should define as D. The intension of Rule1 and Rule2 respectively are：

$$D(Rule)=m_A(x_1)m_B(x_2)m_C(y) \quad (2)$$

$$D(Rule1) = m_{P1}(x1)\ m_{N1}(x2)\ m_O(y) = 0.8\times0.7\times0.9=0.504 \quad (3)$$

$$D(Rule2) = m_{P1}(x_1)\ m_O(x_2)\ m_{P1}(y) = 0.6\times1\times0.7=0.42 \quad (4)$$

Step 3: Combine generated fuzzy rules and expertise ecperience fuzzy rules, and then set up combined fuzzy rules base.

II. OPTIMIZE FUZZY CONTROL SYSTEM WHICH BASED ON GA

Select the appropriate coding method to unified coding for the parameters of membership function and the combined fuzzy rules base , which form a chromosome, to improve the genetic operation and set the objective function, thus optimize the ice fuzzy system.

A. *Encoding parameters*

1) The selection of coding mode

Common GA coding mode contains binary coding, decimal coding, real coding, matrix coding, symbol coding and so on [12]-[14]. The advantages of binary encoding are the simple encoding and decoding operation. The disadvantages are that for some problems of multi-dimensional, high-precision, chromosome encoded string is longer, the search space increases sharply with dimension increases which leads to a large computation. Real coding greatly reduces the string length and improves the efficiency of the algorithm without frequent coding and decoding genetic operation which make its interpretability strong.

2) Membership function coding

To ensure the increasing order of chromosome and generate invalid code string, the distance between its base end is selected as the optimization target. The width of the base of triangular membership function is defined to ensure that adjacent fuzzy partition is not isolated and has little overlap after genetic manipulation.

3) Combined fuzzy rules base coding

All the elements in combined fuzzy rules base were encoded in symbols while 1 to 5 integer values correspond to five fuzzy languages N2, N1, O, P1, P2.

The symbol coding is generated transforming the digitized combined fuzzy rules base to one-dimensional. Combined with membership function and combined fuzzy rules base coding to form a chromosome encoding string.

B. Improvements of genetic operation

1) Improvements of selection

N chromosomes randomly selected to form a new population based on individual fitness and new populations were crossover and mutation in the population of a certain generation. In order to ensure complete population, improve population diversity, expand the search space and prevent the loss of useful gene, we calculated the fitness of each chromosome of the new population, the population operated by crossover and the population by mutation, then selected the best n chromosomes from 3n chromosomes as the next generation population. Which can ensure that the integrity of group, and improve the population diversity, expand the search space and prevent the loss of effective gene.

2) Improvements of crossover

From the perspective of the whole population, for there were large individual differences among populations in the early running GA, choose a larger crossover probability to highlight the role of crossover, thus speeding up the speed of the algorithm. At the same time choose a smaller crossover probability to reduce the likelihood of outstanding individuals destroyed in the late running algorithm because of the small individual differences.

3) Improvements of mutation

Similarly, a smaller mutation probability conducive to the evolution of population in the initial period of running. A greater probability could enhance the diversity of the population and avoid algorithm catching in local optimum in the late running algorithm.

With the above operation, not only the diversities of population could be maintained but also the convergence capabilities of the system.

III. ICE FUZZY SYSTEM WAS OPTIMIZED BY USING GA

In this paper, the monitoring data of ice online monitoring systems of eight transmission lines installed in Guizhou Power Grid in China was selected, mainly includes the ice of IT (*ice thickness*); ET (*environmental temperature*); EH (*environmental humidity*); EW (*environmental wind speed*); CT (*conductor temperature*), which were real-time monitored.

A. Establish an icing fuzzy system

Selecting ET; EH; EW and CT, which transmission line online monitoring system had been monitored as input variables of the ice growth prediction model, the ice thickness of the corresponding value (IT) as the output variable.

The range of input and output variables respectively: ET was -10~10℃, EH was 80~100%, EW was 0~10m/s, CT was -10~10℃, and IT was 0~30mm. And fuzzy division was five level well-distributed triangles.

B. Establish a combined rules base

First of all, the field data of ET; EH; EW; CT and IT were extracted and preprocessed. Then, determining the membership degree of the input and the output in the different universes, and then distributed the maximum membership degree of the input and the output in one universe. Next, generating fuzzy rules with the field data, and calculating the intensity of each fuzzy rule D, counting of the number of the same fuzzy rules and calculating the average strength of the same fuzzy rules. Finally, Using expert experience rules and fuzzy rules which had higher average strength to establish combined fuzzy rules base, as shown in table 1. Selecting higher strength rules when compare the fuzzy rules with expert experience rules, and the strength of the expert experience rules was 0.8.

C. System was optimized by using GA

From the picture 2: Flowchart of icing fuzzy system optimized by GA.

1) Initialize the population

Setting 800 as the population size, 200 as termination evolutionary generation, 0.7 and 0.001 as the crossover probability and mutation probability were respectively.

Table 1: Combined fuzzy rules base

ET	EH	EW	CT	IT	Strength
NB	NB	O	O	NS	0.8000
NB	NS	NB	PS	NB	0.6011
NB	PS	NB	NB	NS	0.8000
NB	PS	NS	O	NS	0.8000
NB	PS	O	O	O	0.4241
NB	PB	NB	NB	PB	0.8000
NS	NS	NS	O	NB	0.8000
NS	NS	PS	O	NB	0.3328
NS	O	NS	O	NS	0.8000
NS	O	O	NS	NS	0.8000
NS	O	O	O	NB	0.2632
NS	O	PS	O	NB	0.8000
NS	PS	NB	NB	NS	0.8000
NS	PS	NB	O	NB	0.4167
NS	PS	NB	NB	O	0.8000
NS	PS	NS	NB	NS	0.8000
NS	PS	NS	O	O	0.8000
NS	PS	O	O	NS	0.8000
NS	PB	NB	NS	PB	0.8000
NS	PB	NS	NS	PS	0.8000
NS	PB	NS	O	O	0.8000
NS	PB	O	NS	NB	0.8000
NS	PB	O	O	PS	0.8000
O	NB	NB	O	NB	0.4445
O	NB	NB	PS	NS	0.8000
O	NB	NB	PB	NB	0.5231
O	NB	NS	PS	NB	0.6823
O	NB	O	O	NB	0.8000
O	NS	NB	PS	NB	0.4721
O	NS	O	PS	NB	0.3348
O	O	NB	NB	NS	0.8000
O	PS	NB	O	NB	0.3840
O	PS	NS	NS	NS	0.8000
O	PS	NS	O	O	0.8000
O	PS	O	O	O	0.8000
O	PB	NB	O	NB	0.2746
O	PB	NB	PS	O	0.8000
O	PB	NS	O	NB	0.8000
O	PB	NS	PS	NS	0.8000
O	PB	PS	O	NS	0.4569
PS	NB	NB	PS	NS	0.5681
PS	NS	NB	PS	NS	0.6466
PS	NS	NS	PS	NB	0.3114
PS	NS	O	PB	NB	0.2467
PS	O	NB	O	NS	0.6374
PS	PS	NB	O	NB	0.4685
PS	PS	NB	PS	NS	0.8000
PS	PS	NS	PS	O	0.8000
PS	PS	O	PS	NS	0.8000
PS	PS	PB	PS	NB	0.8000
PS	PB	NB	O	NS	0.8000
PS	PB	NS	O	NB	0.8000
PS	PB	O	O	O	0.8000
PB	NB	NB	PS	NB	0.3050
PB	NB	NS	PB	NB	0.3391
PB	NS	NS	PS	NB	0.1686
PB	O	NS	PS	NS	0.8000
PB	PS	NS	PB	NS	0.8000
PB	PS	O	PS	NS	0.8000
PB	PB	O	PB	NB	0.8000

2) Coding

There were 60 fuzzy rules and 300 element numbers in the combined fuzzy rules base shown in table 1. Agreeing 1 to 5 integer values correspond to five fuzzy languages NB; NS; O; PS; PB, while limiting code in the range of {1,2,3,4,5}.

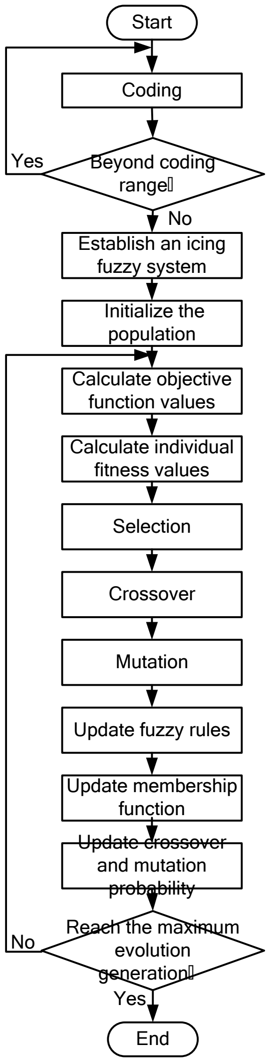

Figure 2: Flowchart of icing fuzzy system optimized by GA

Ice fuzzy system's membership function was coded, for example, the membership function of ET, which coding ranges of the distance between the bottom end were respectively: $a_1 \in (-11,-5]$, $a_2 \in (-5,0]$, $a_3 \in (0,5]$, $a_4 \in (5,10]$. Agreed scope of the distance between the bottom edge end points was [0.8d,1.2d], where d=(10-(-11))/w. Based on first-order inertial time-delay model simulation system, when w was 4 the division of triangular membership functions was feasible [15]. Joint membership function and combined fuzzy rules base coding to form a chromosome encoding string, which length was (4×5)+(5×n)=20+5n, n was the number of rules in combined rules base.

3) The probability of crossover and mutation

The adaptive genetic proposed by M. Srinivas uses a crossover and mutation probabilities with adaptive capacity [16]. In this method, if contemporary adaptation fitness is equaled to the maximum degree, the crossover and mutation probabilities evaluate is 0. Preferred individual almost does not change and outstanding individuals were not the optimal solution for the global optimal solution in the early evolution of the population. So it was easy to fall into local optimization algorithm that this method was very unfavorable for the early evolution. This paper improved adaptive crossover and mutation probabilities, which is calculated as follows:

$$p_c = \begin{cases} 0.8 - \dfrac{(0.8-0.5)(f'-f_{avg})}{f_{max}-f_{avg}} & , f' \geq f_{avg} \\ 0.8 & , f' < f_{avg} \end{cases} \quad (5)$$

$$p_m = \begin{cases} 0.1 - \dfrac{(0.1-0.001)(f_{max}-f)}{f_{max}-f_{avg}} & , f \geq f_{avg} \\ 0.1 & , f < f_{avg} \end{cases} \quad (6)$$

In formula, f_{max}—The largest group fitness value in group;

f_{avg} — The average fitness value of each generation group;

f' — The maximum fitness value of each generation individuals performing crossover operation;

f—The maximum fitness value of each generation individual performing mutation operation.

4) Objective function

Using the minimum value of the sum of the difference between fuzzy system output values of ice and ice monitoring data as objective function, namely:

$$J = \sum_{i=1}^{N} \left| Y_{fuzzy} - Y_{data} \right| \quad (7)$$

In formula, Y_{fuzzy} was ice thickness of ice fuzzy system's output, Y_{data} was monitoring data of icing, N was the number of monitoring data.

5) Individual fitness value

$$Fit(y) = \begin{cases} Cmax - J & , J < Cmax \\ 0 & , other \end{cases} \quad (8)$$

In formula, Cmax was the maximum individual fitness value in population.

D. *Case study*

Selected monitoring data acquired from transmission line online monitoring system on Guizhou Power Grid in 2014, as shown in figure 3, extracting some data and using GA to optimize ice fuzzy system, in another part of the data to validation. Figure 4 is membership function of icing fuzzy system optimized by GA, the membership function of fuzzy partition was no longer homogeneously, more practical. Figure 5 is output surface of icing fuzzy system optimized by GA. Figure 6 is forecasting effect of icing fuzzy system which is optimized by GA, the ice thickness in 0 to 18 mm have higher prediction ability, high accuracy and small error.

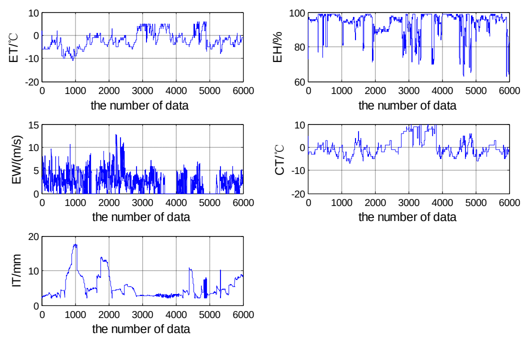

Figure 3: Monitoring data acquired from transmission line online monitoring system on Guizhou Power Grid in 2014

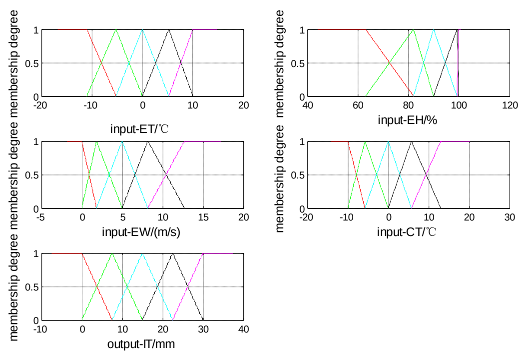

Figure 4: Membership function of icing fuzzy system

optimized by GA

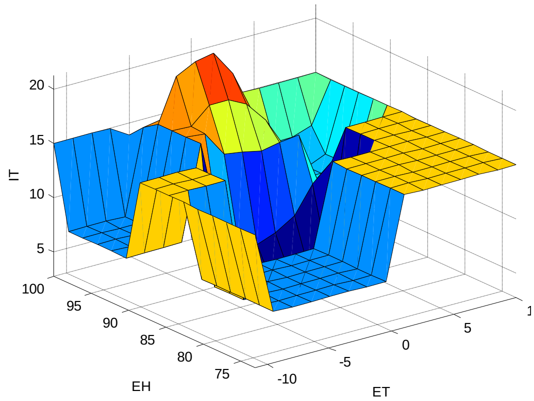

Figure 5: Output surface of icing fuzzy system optimized by GA

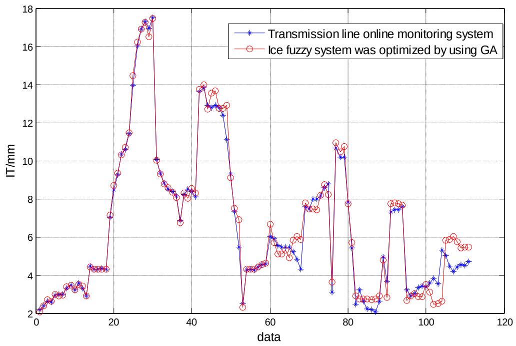

Figure 6: Forecasting effect of icing fuzzy system optimized by GA

IV. Conclusion

In this paper, ice prediction model which based on genetic algorithm and fuzzy logic fusion is established, which had the following advantages: (1) having self-study habits, which can automatically generate fuzzy rules according to on-line monitoring data, and monitoring also had the applicability for unknown;(2) having the self-adaptability, which can be adjusted automatically by the GA ice fuzzy system parameters;(3) having higher prediction accuracy for line ice, which had a certain practical significance.

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