Forecast Model of Transmission Line Sag Based on GA

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Abstract. Transmission lines are an important part of the power system and the main artery for the transmission of electrical energy. The safe operation of overhead lines is critical to the safe and stable operation of the entire power grid. This paper takes the main body of the transmission conductor as the main research object. According to the line load calculation theory, risk assessment theory and fuzzy prediction theory, first establish a transmission line risk assessment model that takes into account the influence of temperature changes under weather forecast, and then uses the GA optimized TS-FNN. The prediction of the sag of the transmission line has verified the feasibility and accuracy of the proposed theory and method through simulation analysis.

Keywords. Transmission line; sag prediction; risk assessment; GA

1. Introduction
With the continuous development of my country's industry, agriculture, and commerce, the electricity consumption of the whole society is increasing day by day, which leads to an increasing demand for power generation, and the requirements for optimized configuration and reliable supply of electricity are also increasing. As a medium connecting power generation, substation, distribution and users, transmission lines are an important part of the power system. Therefore, ensuring the safety of overhead transmission lines is the basis for ensuring the stable operation of the entire power grid.

Transmission lines are exposed to the natural atmosphere all year round, and are often affected by severe weather such as strong storms and rain, ice and snow. However, once severe weather such as strong winds, storms, and icing cause overhead line failures, it has the characteristics of wide spread, long duration, and serious losses, which seriously endangers the safe operation of the power system[1]. Therefore, a countermeasure that can effectively prevent extreme weather from damage to the transmission line is needed to ensure its safe operation, and then the safety and stability of the power grid[2].

This paper studies the prediction of the sag of the transmission line based on the prediction of the refined numerical weather forecast. Taking the transmission line as the research target, establish a transmission line sag prediction model based on weather forecasts, and study the sag of the transmission line under the weather in various scenarios, especially the sag prediction under severe weather conditions, using GA optimized TS-FNN predicts the sag of the transmission line. Provide necessary information support for adjusting the operation mode of the power grid, deploying emergency materials, and formulating rush (overhaul) repair plans to achieve the purpose of early warning, early prevention, and harm reduction [3-4].

2. Blockchain theory and key technologies
The numerical forecast adopts the refined regional numerical forecast system (BJRUCvV3.0), which is based on the mesoscale weather research forecast (WRF) developed and completed. The WRF model system is a new generation of medium-scale research jointly developed and researched by American research departments and universities. Scale prediction model and assimilation system [2]. The
horizontal resolution of the forecast system is 9km, the number of horizontal grid points is 400×649, and the vertical direction is 50 layers. The specific calculation and forecast process is shown in Figure 1.

![Flow chart of BJRUCv3.0 forecast system](image)

**Figure 1.** Flow chart of BJRUCv3.0 forecast system

### 3. Forecast Model of Transmission Line Sag Based on GA

The impact of combined loads under extreme weather has a serious impact on the operational reliability of transmission lines. Research on the risk prediction and assessment of transmission lines has practical significance in preventing line accidents. Based on the random variation characteristics and interference laws of overhead transmission lines’ load-strength Transmission line sag prediction model based on TS fuzzy neural network, and GA is used to optimize various parameters in TTS. Finally, the model calculated by traditional theory is compared The practicality and efficiency of the model are verified through specific application examples.

#### 3.1 The basic concept of combined load under extreme weather

From literature [5], the formula for calculating wind load force per unit length of overhead line conductor is as follows:

$$ F_w = 0.625 \alpha \mu_c \beta_c (d + 2h) \times (kN)^2 \times \sin^2 \theta \times 10^{-3} (N/m) $$

(3-1)

In the formula, $\alpha$ is the wind speed uneven coefficient; $\mu_c$ is the wind carrier type coefficient; $\beta_c$ is the overhead line wind load adjustment coefficient; $d$ is the outer diameter of the overhead line; $h$ is the thickness of ice coating; $V$ is the wind speed; $k_N$ is the air density; $\theta$ is The angle between the wind direction and the line direction.

The dead weight load per unit length of the overhead line is

$$ F_r = 9.80665 \times P_l (N/m) $$

(3-2)

Where is the mass per unit length of the overhead wire.

The ice load per unit length of the overhead line is:

$$ F_i = 9.80665 \times 0.9 \pi b (b + d) \times 10^{-3} (N/m) $$

(3-3)

In the formula, $b$ is the thickness of ice coating; $d$ is the diameter of the overhead wire.

According to literature [6] and literature [7], the formula for calculating rain load force per unit length of overhead line conductor is as follows.

$$ F_r = \frac{2}{9} \pi d^3 nb V_s^2 $$

(3-4)

Where: $d$ is the raindrop diameter; $n$ is the number of raindrops per unit volume; $b$ is the width of the line's rain surface; $V_s$ is the load risk modeling of overhead transmission lines under severe weather with raindrops and predicts the speed before falling to the ground.
Considering extreme weather such as maximum icing, storm, strong wind, low temperature, etc., the formula for calculating the combined load per unit length of the overhead line is:

\[
F = \begin{cases} 
\sqrt{(F_i + F_b)^2 + F_t^2} & \text{ Maximum icing} \\
\sqrt{F_i^2 + F_t^2} & \text{ Gale} \\
\sqrt{(F_i + F_b + F_t)^2 + F_t^2} & \text{ storm} \\
\sqrt{F_i^2 + F_t^2} & \text{ Low temperature}
\end{cases}
\]

(3-5)

3.2 Line unreliability calculation model

According to the risk analysis model under the action of ice and wind load on the line [2], an analytical model for risk assessment of various combined loads on overhead lines under extreme weather is established. According to the calculation theory of structural unreliability, random variables are used to deal with line strength when calculating line reliability. In severe weather conditions, the line load changes with time, so the load can be regarded as a variable that changes with time. The specific expression is shown below.

\[
S(t) = f(F(t), R) = R - F(t)
\]

(3-6)

In the formula, \( R \) is the design strength of the line; \( F(t) \) is the actual load on the line. When the structure function value is greater than zero, it means the line is working normally; when the structure function value is less than zero, it means the line is faulty. Suppose the line strength is \( R \), and the probability of the line in normal working condition under a certain load is

\[
P(R > F(t)) = f_{F(t)}(q) \int_{q_0}^{\infty} f_R(r) dr
\]

(3-7)

Derived from the above formula, when the load on the line is an arbitrary value, the unreliability calculation formula is as follows:

\[
P_r = 1 - \int_{q_0}^{\infty} f_{F(t)}(q) \int_{r_0}^{\infty} f_R(r) dr dq
\]

(3-8)

In the above formula, \( f_R(r) \) represents the probability density function of the design strength of the line; \( f_{F(t)}(r) \) represents the probability density function of the stress on the line.

3.3 Sag prediction of transmission line

TS-FNN system combines fuzzy theory and neural network, so it not only has the advantage of fuzzy logic that fuzzy theory is good at expert knowledge, but also has the advantage of neural network distributed access. The working principle diagram of the transmission line risk prediction system constructed in this paper is shown in figure 2.

![Diagram of risk prediction system](image)

**Figure 2** Display of risk prediction system

The T-S fuzzy neural network is composed of two parts: the antecedent network and the subsequent network.
The antecedent network consists of 4 layers. The first layer is the input layer, and its function is to transfer the input value \( x = [x_1, x_2, \ldots, x_n]^T \) to the next layer. The second layer is the membership function layer, its function is to store the membership function, the expression is shown in formula (3-9).

\[
\mu^i_a = \mu^i_a(x_i) = \exp \left[ -\frac{1}{2} \left( \frac{x_i - c_{ia}}{\sigma_{ia}} \right)^2 \right]
\]  

(3-9)

In the formula, \( c_{ia} \) is the center of Gaussian membership function; \( \sigma_{ia} \) is the mean square error.

The third layer is the fuzzy rule layer. Its function is to pair the antecedents of the fuzzy rules, and then calculate the fitness of each fuzzy rule according to formula (3-10).

\[
\alpha_j = \mu^1_1 \mu^2_2 \ldots \mu^m_m
\]  

(3-10)

The fourth layer is the normalization layer, and its function is to normalize the data according to formula (3-11).

\[
\overline{\alpha}_j = \alpha_j / \sum_{i=1}^{m} \alpha_i, \quad j = 1, 2, \ldots, m
\]  

(3-11)

The subsequent network consists of 3 layers. The first and second layers are the input layers, whose function is to calculate the consequence of each rule according to formula (3-12)

\[
y_{ij} = p^j_{i0} + p^j_{i1}x_1 + \ldots + p^j_{in}x_n = \sum_{i=0}^{n} p^j_{ij}x_i
\]  

(3-12)

\( j = 1, 2, \ldots, m; \quad i = 1, 2, \ldots, r \)

The third layer is the output layer. Its function is to output the output results of the system. The calculation formula is shown in formula (3-13), where represents the weighted average of each rule consequence.

\[
y_i = \sum_{j=1}^{m} \alpha^-j_y_{ij}, \quad i = 1, 2, \ldots, r
\]  

(3-13)

Define the square error as:

\[
E_p = \frac{1}{2} \sum_{i=1}^{r} (t_i - y_i)^2
\]  

(3-14)

In the formula: \( t_i \) and \( y_i \) represent expected output and actual output.

4. Simulation

After the relevant algorithm program is compiled using MATLAB integrated development environment, a certain section of specific overhead transmission line is selected as a calculation example, and the experimental simulation is carried out using the GA optimized TS-FNN prediction model proposed in this paper. The simulation line is a 220kV overhead transmission line, passing through a typical meteorological area VIII, the safety factor of the line is 2.5, and the maximum service stress control meteorological condition (set the span as L): L<107.5m, the minimum temperature is the control condition; 107.5m< L<139.5m, the annual average temperature is the control condition; L>139.5m, the thickest icing is the control condition. Then bring the data into the new method based on GA optimized TS-FNN and adaptive FNN method proposed in this article, and show the results as shown in Figure 3.
Figure 3 Comparison of GA-FNN and adaptive FNN prediction results

Figure 3 shows the comparison of GA-FNN and adaptive FNN prediction results. The figure shows that the accuracy of GA-FNN's prediction results is higher than that of adaptive FNN. Therefore, the following conclusions can be drawn:
(1) Improved the training speed through GA improvement.
(2) Compared with FNN, GA-FNN is not easy to fall into a local optimal solution and has strong classification ability.
(3) The GA-FNN prediction results are basically consistent with the theoretical calculation results, but the theoretical analysis model needs to consult the Gaussian distribution value. Therefore, GA-FNN is accurate and more convenient.

5. Conclusions
The main research object of this paper is the power line of the transmission line. Firstly, the refined numerical forecasting technology is introduced based on the line design theory, and then combined with the combined load model of the transmission line and the line unreliability calculation model, the load risk of the transmission line under extreme weather is evaluated. Analyze the failure probability and failure probability of transmission lines under certain meteorological conditions. The sag prediction of the transmission line is carried out by predicting the characteristic value of the meteorological data, and different sag prediction results are given. The obtained sag prediction curve is very close to the actual curve, which further demonstrates the feasibility of the model in this paper. It provides new methods and ideas for future sag prediction.

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