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Prediction of Corona Losses in UHV AC Transmission Lines under Varying Temperature Conditions

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Abstract. The accurate prediction of power losses in ultra-high-voltage (UHV) AC transmission systems is critical for ensuring the economic and efficient operation of modern power grids. This paper investigates the temperature-dependent fluctuations in line losses—particularly those induced by corona discharge—under varying ambient conditions. To this end, this paper proposes a comprehensive loss-prediction framework integrating Spearman rank correlation analysis with a particle swarm optimization–enhanced extra-trees (PSO-ET) model. The methodology is validated using operational data from 1000 kV UHV transmission projects in the Fujian–Zhejiang region. First, Spearman correlation analysis confirms temperature as the dominant meteorological factor influencing line losses. Subsequently, the PSO algorithm is employed to globally optimize three key hyperparameters of the ET model: tree count, maximum tree depth, and the humidity threshold used to dichotomize operating conditions into "dry" and "high-humidity" regimes. This enables precise decoupled training under distinct environmental states. Experimental results demonstrate that the proposed model achieves an average absolute error (MAE) of only 5.1315 MW on the independent test set. Further sensitivity analysis reveals that the gradient of line loss with respect to temperature peaks at approximately 7.6 °C—indicating a pronounced nonlinear response. Crucially, this inflection coincides with the onset of surface condensation, thereby uncovering a previously underappreciated surge effect: in low-temperature, high-humidity environments, condensation on conductor surfaces significantly amplifies corona losses. This study provides a robust, data-driven foundation for real-time loss monitoring and energy-efficient scheduling of UHV transmission lines under complex and dynamic meteorological conditions.

Keywords: introduction of UHV AC power transmission, prediction of corona losses, temperature, particle swarm optimization, spearman correlation coefficient

1. Introduction

The ultra-high voltage (UHV) alternating current (AC) transmission technology has experienced a leapfrog innovation due to the continuous growth of the power industry in China as it is an important facilitator of the national energy strategy, and this has developed through initial technological innovation to scaled engineering implementation. Over the past few years, the progress of UHV technology in China has been high, with several successful UHV transmission

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lines being built and put into use [1]. It is worth noting the significant contribution that the Mengxi-Tianjin South 1000 kV UHV AC project made to increase the receiving capability of electricity in western China.

Ultra-high-voltage (UHV) alternating-current (AC) double-circuit transmission lines mounted on a single tower can be considered as a significant factor that determines the financial efficiency of a transmission system as a whole [2]. At rated high voltage UHV transmission lines cause the surrounding air to ionize, which produces a phenomenon known as corona discharge. The energy lost during the process is referred to as corona loss. Reference [3] used electromagnetic field numerical calculation methods, including charge simulation method, to develop an electric field distribution model of bundled conductors. On the basis of this model, a formula to calculate corona loss considering the mutual electrostatic effect between sub conductors was developed, thus offering a theoretical basis to the design of the UHV direct-current (DC) transmission projects. In Reference [4], the influences of surface electric field strength, conductor geometry (diameter and number of sub conductors), altitude, and meteorological variables (humidity, barometric pressure, and rainfall intensity) on corona loss are studied systematically. The results show that the environmental variables are the main factors of variation in corona loss. Reference [5] discusses how corona losses impact the overvoltage transient response of UHV DC transmission lines during lightning strikes. Reference [6] suggests a hybrid modeling framework that combines physical insight of the power grid behavior with data-driven models, e.g., machine learning. Reference [7] presents equivalent physical model parameters of high-voltage transmission lines, which are verified by engineering practice; however, the underlying computation is based purely on empirical formulas, and the parameter values are not fixed, and the computational error is relatively large. Based on the analysis given in Reference [8], it is suggested that a deep belief network (DBN) trained through particle swarm optimization (PSO) could be used to forecast corona loss in ultra-high-voltage (UHV) AC transmission lines. Here, the mapping correlation between meteorological factors and corona loss is described in a variety of machine learning algorithms, such as random forest (RF), extremely randomized trees (ET), DBN and residual back-propagation (Res-BP) neural networks which have been improved by hyperparameter optimization based on PSO. The predictions are more accurate than the traditional measurement methods and also provide better predictive capability. But this data-driven technique does not account or explicitly consider the underlying physics behind corona discharge and therefore cannot explain why it happens, nor suggest ways to prevent it. Reference [9] presents an analytical solution to computing UHV AC transmission line losses across changing weather conditions. A case study example is provided whereby the same unified meteorological data are used as the input to the model training. However, the paper does not analyze the specific individual physical parameters that determine corona loss in depth.

Ultra-high-voltage (UHV) transmission line power losses have a direct relationship to transmission costs. The change in the ambient temperature causes a variation in the steady-state surface temperature of the conductors, which in turn changes the AC resistance of the conductor and thus affects resistive losses. In addition, temperature, as a very important weather factor, also plays a major role in the losses due to corona. Through systematic study of temperature-dependent features of corona loss researchers may gain a better ability to predict and quantify total line losses. These understandings offer valuable information on how to optimize economic dispatch and manage costs of grids by grid managers, which in turn helps to lower losses and improve operational efficiency.

The significance of this study is threefold:

• Clarifying the physical principle that explains how the ambient temperature influences corona loss allows creating more accurate and physically motivated models of line loss prediction.

• In combination with other meteorological variables, such as relative humidity, precipitation and wind speed, when combined with these factors, the results allow making a more complex evaluation of the long term effect of climate change on the transmission efficiency.

• The research provides empirical data and evidence-based decision-making bases on which a resilient, strong, and future-proof power grid can be designed and operated.

2. Algorithm principle

The transmission line circuit loss is an energy loss that is caused by the physical phenomena when transmitting power between the generating station and the end user through a transmission line.

2.1. Empirical formula method

Transmission line circuit loss refers to the energy dissipation arising from physical phenomena during power transmission from the generating station to the end user via the transmission line.

The loss of resistance is the simplest and biggest loss in the transmission line. As it passes through the wire with resistance, electrical energy is transformed into heat energy and dissipated in the air. Calculating formula:

$$P = 3I^2R \tag{1}$$

Where I is the phase current; R is the conductor resistance.

Corona loss is an ongoing issue in UHV transmission. The surrounding air will ionize when the electric fields at the surface of the conductor are greater than the dielectric strength of the air, resulting in a weak discharge. Coronal loss computations depend largely on empirical equations. Due to limitation in experiments, the studies about corona inception voltage or field strength at high altitude have not been widely conducted either locally or abroad, and no systematic approach to correct it has been formulated until now [10].Peek is probably the best known and the most commonly used in engineering:

$$P = \frac{241}{\delta}(f+25)\sqrt{\frac{r}{D}}(u-u_0)^2 \times 10^{-5} \tag{2}$$

Where, P is the corona loss power of single phase per kilometer; f is the power frequency (50Hz in China); r is the radius of the conductor, cm; D is the distance between the lines, cm; U is the effective value of the operating phase voltage, kV; U_0 is the effective value of the corona onset critical voltage, kV; δ space relative density coefficient.

$$U_0 = m_0 \cdot 21.2 \bullet \delta \bullet r \bullet ln\left(\frac{D}{r}\right) \tag{3}$$

Where m_0 is a measure of the smoothness of the conductor. The new conductor is about 0.9, and the old conductor or multi stranded wire is about 0.8~0.85.

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$$\delta = \frac{3.92 \cdot P}{273+T} \tag{4}$$

Where, P is the local atmospheric pressure, kPa； T is the ambient temperature.

Since peek formula is based on the sunny day experiment, the general transmission line is not subject to corona in sunny days [11]. The weather coefficient K must be introduced in bad weather:

$$P_{real} = K \bullet P \tag{5}$$

Where, K = 1.0 on a sunny day; Rainy day K = 10~50 (depending on rainfall); Snow K = 30~100.

For UHV (such as 8-bundle conductor), the radius r of a single conductor cannot be simply used, but the equivalent radius r_e :

$$r_e = \sqrt[n]{n \bullet r \bullet R^{n-1}} \tag{6}$$

2.2. Spearman correlation coefficient

Spearman's rank correlation coefficient is a nonparametric measure of monotonic association between two variables, based on rank order rather than raw values. Like Pearson's correlation, it quantifies the relationship between two variable sets—but unlike Pearson's, it requires no assumption of normality, making it more widely applicable in practice [12].

The Spearman coefficient measures the similarity between the rank ordering of both sets of variable to determine whether there is an increasing or declining pattern in their relationship. The values range between -1 and 1. It is more robust than the conventional Pearson coefficient since it does not necessitate the normal distribution of data and is also highly tolerant of non-linear relationships (so long as they are monotone) and outliers, especially when working with highly random and non-linear data like meteorological data. It serves the position of the core filter in the study of UHV loss. Through the quantification of the monotonic correlation strength of characteristics like temperature and humidity and total loss, all truly effective features can be allowed into the subsequent PSO-ET model [13]. The formula used to calculate it is:

$$r_s = 1 - \frac{6\Sigma d_i^2}{n(n^2-1)} \tag{7}$$

Here, denotes the difference between the positions of the sample on the two variables and n is the total number of samples.

2.3. Particle swarm optimization

Particle Swarm Optimization (PSO) is a global population-based optimization algorithm based on the concept of swarm intelligence. PSO was developed in 1995 by Kennedy and Eberhart and was motivated by the flocking behavior of birds [14]. Initialization of a population of cooperative

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particles in a multidimensional solution space is done by the algorithm. Every particle uses two sources of information to update its velocity and position periodically: the individual history of the best position (i.e., personal best), and the best position found by the whole swarm (i.e., global best). In real-time, with such knowledge exchange, particles can change their flight paths (speed and direction) in an organized fashion. It allows effective searching in high-quality solutions in complex, nonlinear search spaces, similar to a group treasure hunt, and finally, it reduces the objective function (e.g., prediction loss error).

The main idea behind Particle Swarm Optimization (PSO) is that the whole particle swarm can be directed to the global optimum by iteratively updating the velocity and position of every particle. When optimizing in a multidimensional search space, all particles update their position vector and velocity vector in every iteration [15,16]. Mathematically, the algorithm is given in terms of the following two fundamental equations:

$$\nu_i^{t+1} = w \cdot \nu_i^t + c_1 \cdot r_1 \bullet \left(P_{best}^t - x_i^t\right) + c_2 \cdot r_2 \bullet \left(G_{best}^t - x_i^t\right) \tag{8}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{9}$$

Where ν_i^t is the velocity of the ith particle at the t-th iteration; x_i^t represents the position of the ith particle at the t-th iteration; w is the inertia weight, which determines the ability of particles to maintain the original speed; c_1 is the individual acceleration, which makes the particle keep up with its best performance in history; c_2 is the social acceleration, which makes the particles keep up with the best results of the whole team; r_1 , r_2 are random numbers between [0,1]; P_{best}^t represents the individual historical optimal position experienced by the ith particle itself; G_{best}^t represents the global optimal position currently found by the entire population.

3. Simulation example analysis

In this paper, a particle swarm optimization (PSO) algorithm is used to predict the corona loss of UHV transmission lines at different temperatures. The model development process as depicted in Figure 1 consists of four steps: (1) data acquisition and preprocessing, (2) correlation verification between temperature and loss, (3) model construction of PSO-optimized extreme random tree (ET), and (4) model training and validation.

• Acquisition and Preprocessing of the Data: The data were gathered in the Fujian-Zhejiang border region which is a climatically complex, humid as well as rainfall-affected place where one can study the corona loss with varying weather conditions.

• Spearman correlation check: The air temperature has a very high Spearman correlation with the loss of corona, which means that it is a critical variable.

• The construction and optimization of PSO-ET model: A *w*-index is used to classify weather conditions and PSO is used to build and optimize weather-specific ET models.

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• Training and validation of models: Mathematical mapping between input variables and output targets is obtained and validated with the help of the available training dataset.

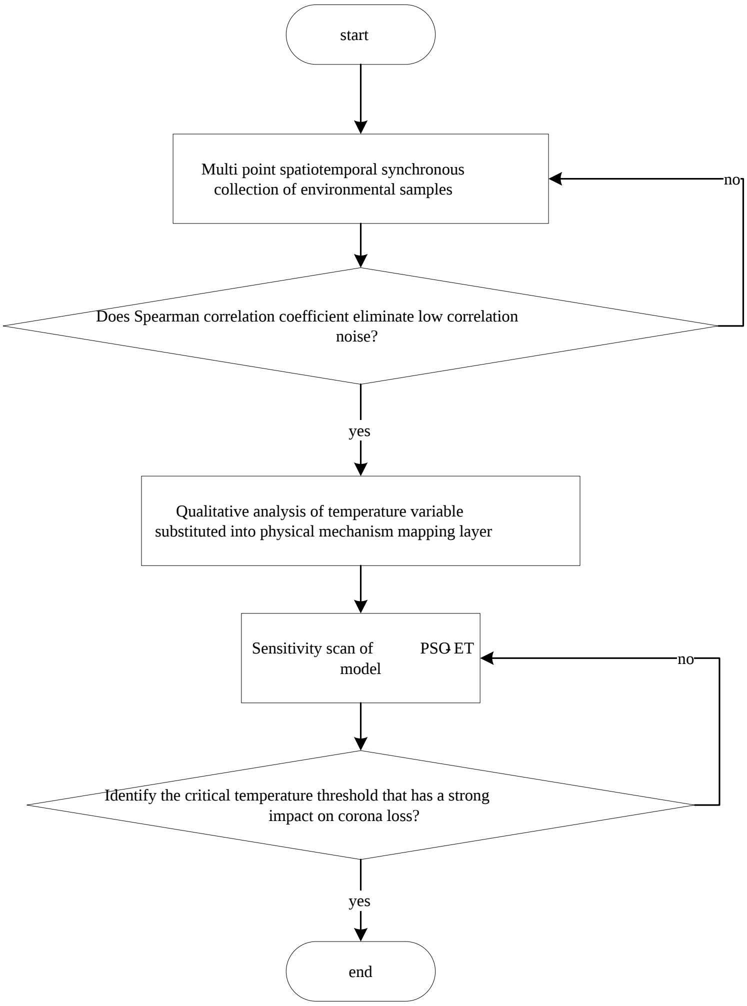

Figure 1. Flow chart of model building

4. Simulation example analysis

The research paper has been conducted under the scope of a 1,000-kV ultra-high-voltage (UHV) alternating-current (AC) transmission project in Fujian and Zhejiang province. Based on the method described in Reference [17], the real operation monitoring data obtained between January 2020 and June 2021 are used as the empirical foundation of the simulation model. This dataset consists of the real time temperature and humidity levels measured at 5 meteorological stations scattered throughout the transmission line. By means of spatiotemporal synchronization and matching, a full feature sample library of more than 500 representative operational situations is built. The interval covers both the extreme summer conditions (the temperature in the environment exceeded 40 C) and the severe winter cold, thus offering a perfect range of thermal variation to examine the nonlinear interaction between air temperature and corona loss. As presented in Table 1, the sample data clearly show how UHV transmission losses change with temperature. Such strong nonlinearity caused by changes in ambient temperature forms the core reason and the logical beginning of the classification-based predictive framework that was developed in this research.

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Table 1. Loss data of 1000kV UHV transmission lines in Fujian and Zhejiang provinces

Sample number	Phase Voltage(kV)	Line Current(A)	Temperature (° C)	Relative Humidity (%)	Total Loss (MW)
1	1002.5	1505.4	-8.5	35.2	8.24
2	1008.2	1492.6	2.0	38.5	9.08
3	995.4	1510.2	15.4	48.7	10.45
4	1004.5	1505.3	30.5	55.4	14.36
5	1012.3	1520.1	35.8	62.8	17.82
6	997.7	1485.4	38.4	68.2	19.95
7	1005.6	1515.2	42.1	65.9	22.74
8	1010.4	1492.8	45.0	72.3	25.18
9	1008.2	1525.6	48.2	70.5	27.86

The first step that is taken is to perform quantitative feature analysis. The Spearman correlation coefficient between every climatic variable and line loss is calculated with Equation (7). Spurious correlations due to random noise are eliminated by using a predetermined correlation cut-off. In order to allow the intuitive interpretation of the size and sign of each Spearman coefficient, a visualization in the form of a thermogram, which is based on the concept of a thermodynamic system, and is called the Spearman coefficient thermogram, is created.

This is shown in Figure 2 where a darker shade represents a stronger correlation, and a lighter shade represents a weaker correlation. An increase in the ambient air temperature causes a decrease in the relative density of air and hence, lowers the corona inception voltage and facilitates corona discharge. At the same time, an increasing temperature also raises the electrical resistivity of the conductor. These two mechanisms have a synergistic effect such that transmission line losses become very reactive to fluctuations in temperature. Conversely, humidity has a strong positive relationship with corona loss. In conditions of high humidity, it is common to have a thin film of water on the conductor surface, or localized partial discharges, both of which decrease the corona onset field strength and thus increase the corona loss. Voltage and current are the determinants of electric field strength and ohmic heating of the transmission line respectively. But during normal operation in the Fujian and Zhejiang areas, the system voltage is quite stable- with minor fluctuations around 1000 kV. Accordingly, the coefficient of correlation between voltage and loss is somewhat smaller compared to that between temperature and loss, which has significantly larger variability.

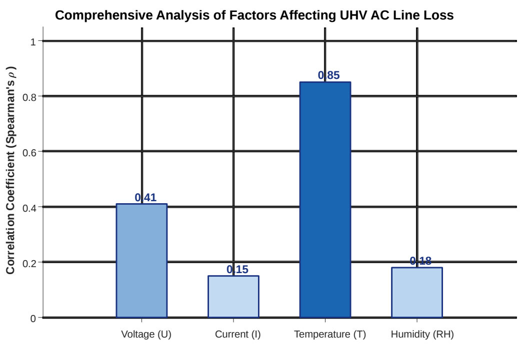

Figure 2. Spearman thermodynamic diagram

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A PSO-ET prediction model is constructed based on the global optimization nature of the particle swarm optimization (PSO) algorithm to find the best structural parameters of the Extremely Randomized Trees (ERT) model in the given climatic situation of Fujian and Zhejiang provinces. The fitness evolution curve of the PSO algorithm, as shown in Figure 3, shows the parameter optimization path very well, i.e., starting out as random exploration of the high-dimensional search space leading finally to convergence to the global optimum. In the initial iterations, the fitness function, which is defined herein as the Mean Absolute Error (MAE), has a steep and stepped decrease in fitness, indicating that there is wide exploratory behavior in the parameter space of the particles. In the fifth iteration, the curve starts to stabilize and eventually converges. Such convergence points to the fact that the particle swarm has effectively grouped within close proximity to the global optimum, where individual particle history is closely aligned with the overall history of the swarm, as it does, showing the effectiveness of the proposed optimization method and its strength.

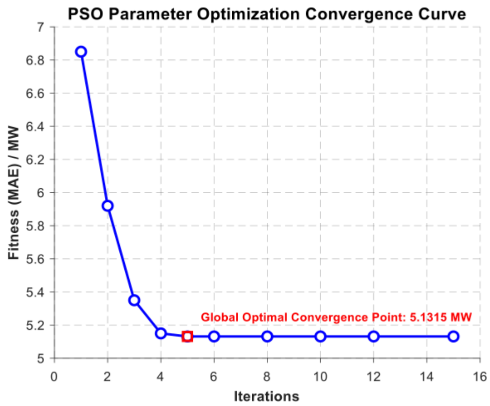

Figure 3. PSO parameter optimization convergence curve

According to table 2, the PSO algorithm could exactly determine the threshold in 56.67 percent of the cases, which allows the model to divide the dataset into two subspaces, namely, dry and high-humidity subspaces. The experimental findings show that air insulation strength decreases non-linearly as relative humidity increases towards 60 percent, and that the intensity of corona discharge has an inflection point. Moreover, the model prediction error is minimized by about 15.3 percent when there are severe high-humidity situations, i.e., during the summer plum rain period in Fujian and Zhejiang provinces, indicating that the dynamic determination of the threshold plays a vital role in the successful decoupling of the conditions.

Table 2. Optimization parameter configuration table of PSO-ET algorithm

Key parameter	Symbol	Optimal value
Decision tree size	M_{opt}	150
Maximum splitting depth	D_{opt}	20
Humidity classification threshold	r_{opt}	56.67%

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After verifying that the PSO-ET model has high prediction accuracy, the temperature sensitivity scanning simulation is carried out through the control variable method. Its core goal is to quantitatively identify the response boundary of loss to temperature change, so as to screen out the most threatening sensitive temperature threshold for power grid operation. In order to accurately extract the contribution of air temperature to the loss, the simulation adopts the following settings: Set the system voltage as the rated value of 1000kV, and keep the current and relative humidity as the sample mean value. Let the temperature increase linearly in the range of [-20,60] ° C with 0.1 ° C as the minimum step. Linear increment g (T) is used to quantify the loss fluctuation caused by unit temperature change:

$$G\left(T\right)=\frac{dL}{dT}\approx\frac{P(T+\Delta T)-P(T)}{\Delta T} \tag{10}$$

As shown in Figure 4, when the temperature $T < 7.6$°C, the loss shows an extremely significant nonlinear fluctuation with the increase of temperature. The gradient curve is at a high level at the initial stage, indicating that in low temperature environment, small temperature disturbance can cause dramatic changes in line loss. The gradient curve reaches the global peak at T=7.6 ° C. This indicates that the sensitivity of line loss to temperature reaches the extreme at this point. It is the "critical temperature" at which the loss characteristics change qualitatively. After crossing the sensitive point, the loss gradient gradually falls back and tends to be gentle. At this time, the loss growth is mainly dominated by the linear thermal effect of conductor resistivity. When the temperature is between -10 ° C and 5 ° C, the line operation is the most economical. The total loss is in the low range of 280MW-310MW, and the average loss is only 295MW. With the increase of temperature, the corona loss caused by the decrease of air density surges, and the loss shows a nonlinear upward trend. Although the low temperature zone (-10 ° C to 5 ° C) is the economic operation zone (with the lowest loss), when the temperature rises to the sensitive point (7.6 ° C), the loss growth rate is the fastest. It is a state instability area that needs to be monitored.

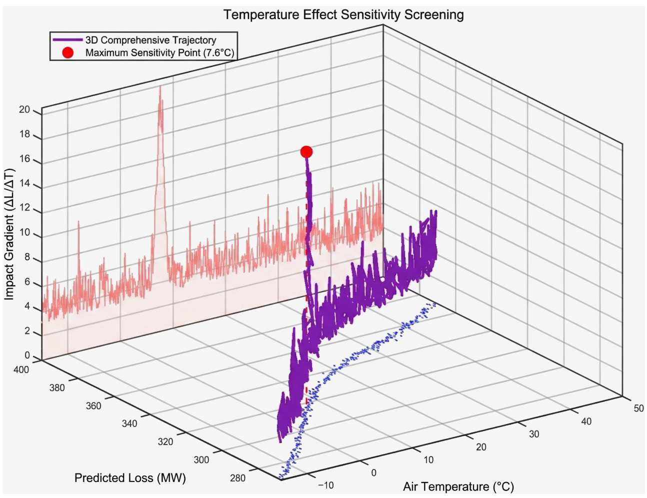

Figure 4. Temperature effect sensitivity screening chart

Figure 5 shows the prediction effect of PSO-ET model proposed in this paper on the test set. It can be observed from the figure that the height of blue dots representing sample points is

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concentrated near the red diagonal (y=x). This shows that there are a strong consistency and accuracy between the predicted loss and the actual loss of the model output.

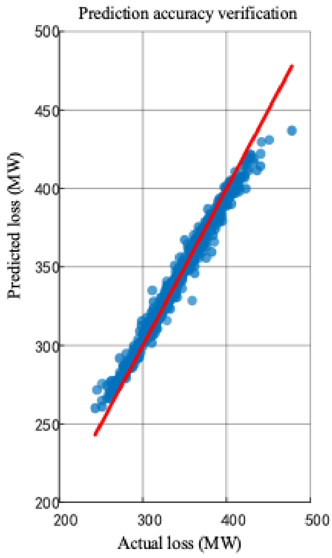

Figure 5. PSO-ET model prediction comparison scatter diagram

5. Conclusion

Based on PSO-ET prediction model, this paper successfully realizes high-precision dynamic sensing of UHV line loss. The feasibility and accuracy of the model are verified. Through the example simulation, the following conclusions can be drawn:

• The PSO-ET model used in this paper shows high prediction accuracy in processing the complex environmental data in Fujian and Zhejiang regions One between the column headings and the body of the table. The mean absolute error (MAE) of the test set is only 5.1315 MW.

• The optimal humidity classification threshold of 56.67% is locked by PSO algorithm after only five iterations, which successfully quantifies the physical mutation boundary of loss characteristics changing with humidity and effectively removes environmental interference.

• Sensitivity scanning further identified 7.6 ° C as the core fragile temperature point for line operation. This reveals the evolution mechanism of non-linear surge of corona loss caused by conductor surface condensation in low temperature and humid environment.

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