2023 International Conference on Smart Electrical Grid and Renewable Energy (SEGRE) | 979-8-3503-2326-9/23/$31.00 ©2023 IEEE | DOI: 10.1109/SEGRE58867.2023.00058

Forecast Overhead Transmission Lines Icing Based on Weighted Regression of Multiple Meteorological Factors

1st Xiaowei Huai*
Hunan Disaster Prevention Technology Co., Ltd.
State Key Laboratory of Disaster Prevention and Reduction for Power Grid
Changsha, China
huaixw@foxmail.com

2nd Bo Li
Hunan Disaster Prevention Technology Co., Ltd
State Key Laboratory of Disaster Prevention and Reduction for Power Grid
Changsha, China
292785038@qq.com

3rd Linwei Huang
Hunan Disaster Prevention Technology Co., Ltd.
State Key Laboratory of Disaster Prevention and Reduction for Power Grid
Changsha, China
756601613@qq.com

4th Shenglin Liu
Changsha Rail Transit Group Co. Ltd
Changsha, China
295357558@qq.com

5th Siguo Zhu
Disaster Prevention and Reduction Center of Hunan Electric Power
State Key Laboratory of Disaster Prevention and Reduction for Power Grid (acronyms: SKLDP&RP),
Changsha, China
124763400@qq.com

6th Ke Hu
Changsha Rail Transit Group Co. Ltd
Changsha, China
huk@hncsmtr.com

***Abstract*—Accurate prediction of icing thickness on overhead transmission lines is crucial for ensuring the reliable operation of power transportation systems. In this study, we propose a novel approach based on weighted regression using multiple meteorological parameters to forecast icing thickness. The method leverages numerical modeling to obtain meteorological parameter predictions and employs statistical analysis to construct a predictive model. By integrating real-time monitoring data, our approach achieves a mean prediction error of approximately 0.5mm for icing thickness, outperforming the Makkonen model with an average error of around 1mm. The results demonstrate the effectiveness of our proposed method in accurately forecasting icing thickness. This research contributes to the advancement of scientific knowledge in the field of overhead line icing and offers valuable insights for optimizing prediction models and enhancing the resilience of power transmission systems.**

Keywords-overhead transmission lines; icing; prediction methods; numerical weather prediction; weighted regression model, renewable energy application

I. INTRODUCTION

Transmission lines are an important component of the power system; however, the issue of icing on transmission lines often poses a threat to the stable operation of the power system [1]. Icing increases the load on transmission lines, leading to overloading or even causing faults such as short circuits. It can even result in tower collapse and line breakage, causing significant economic losses and safety risks to the power system. The widespread and prolonged rain, snow, and ice disasters experienced in southern China in 2008 affected over 100 million people and caused over 700,000 tower collapses [2]. It not only impacts the power system but also affects railway and rail transit overhead contact systems, resulting in train disruptions and significant disruptions to public transportation, thereby having a significant societal impact. In 2020, the northeastern region of China experienced rain, snow, and ice disasters, leading to icing on multiple high-speed and conventional railway overhead contact systems within the Shenyang Railway Bureau, with an affected range of 4,677 kilometers (1,942 kilometers for high-speed railways and 2,735 kilometers for conventional railways), significantly affecting railway transportation operations..

To mitigate the risks associated with icing on transmission lines, the prediction of icing on transmission lines has become an important task. The objective of transmission line icing prediction is to accurately forecast the potential icing conditions on transmission lines based on weather forecasts and meteorological observations. This provides timely decision support to power system operators, ensuring the safe and stable operation of the power grid [3]. Commonly used models for predicting icing on overhead transmission lines can be categorized into physical models and statistical models. Physical models, such as the Jones model [4], Makkonen model, and others [5-6], simplify the physical mechanisms of icing by capturing the freezing of supercooled water droplets upon collision with the conductors. These models have been widely applied in engineering. In statistical models, researchers have used various predictive factors to establish multivariate linear regression, stepwise regression, and other equations, achieving certain results [7-8]. In recent years, machine learning algorithms have also been introduced into icing prediction, such as artificial neural network discriminant analysis models based on the backpropagation (BP) algorithm and icing prediction models based on support vector machines, which have achieved certain levels of effectiveness in icing prediction.

The establishment of prediction models requires analysis and modeling of a large amount of actual measurement data. There are two sources of observed data on the icing thickness of overhead transmission lines: simulated artificial icing of conductors or icing thickness data obtained from icing monitoring devices. The former often exhibits significant discrepancies between simulated conductor data and actual conductor icing data, with limited data and insufficient representativeness. The latter is prone to systematic biases or outliers due to the diverse principles of monitoring instruments.

In this paper, based on data from icing monitoring devices, a prediction model for icing on overhead transmission lines is proposed, which utilizes weighted regression of multiple meteorological factors. By increasing the weight of residuals in the multivariate linear regression equation and using weighted least squares to obtain optimal weights, this model eliminates the influence of abnormal data and systematic biases from monitoring devices, achieving more accurate results compared to traditional physical models.

II. DATA AND METHOD

A. Data

The icing data used in this study were obtained from icing monitoring devices installed on transmission towers of the provincial power grid. In early 2021, a polar vortex southward movement resulted in a significant drop in temperatures. Influenced by cold wave weather and warm moist airflow, the icing process during this period was extensive, with high icing intensity. The icing was mainly concentrated in the eastern and northwestern parts of the province. Table 1 provides the time, observed coordinates (longitude and latitude), and maximum icing thickness recorded at monitoring point A (104.07°E, 27.85°N). From the table, it can be observed that on January 8, 2021, the ice thickness was 0.8 mm. Subsequently, there was a rapid increase in ice accretion on January 9. The maximum ice accumulation thickness occurred on January 10, 2021. Afterwards, the observed icing thickness gradually decreased. In this study, a total of 247 monitoring points were used, and after quality control, eliminating nine clearly abnormal monitoring points, data from 238 monitoring points were retained for icing thickness measurements.

TABLE I. TIME AND MAXIMUM ICING THICKNESS

Date	*Lon*	*Lat*	*Icing thickness（mm）*
2021-01-08	104.07	27.85	0.8
2021-01-09	104.07	27.85	2.6
2021-01-10	104.07	27.85	3.0
2021-01-11	104.07	27.85	2.6

B. Method

The Makkonen model is recommended by the International Standard for Icing on Overhead Lines (ISO 12494-2017) and performs well in simulating rime icing. The Makkonen icing model can be expressed by the following equation:

$$\frac{dM}{dt} = \alpha_1 \alpha_2 \alpha_3 w A v \tag{1}$$

In Equation (1), M represents the ice mass per unit length, α_1 is the collision efficiency, which is believed to be related to wind speed. α_2 represents the viscosity, which has a nonlinear relationship with wind speed. α_3 is the freezing rate, which is considered to be related to temperature. The parameter w represents the liquid water content per unit volume, which is related to relative humidity. A represents the cross-sectional area of the icing body, and v represents the wind speed perpendicular to the icing object.

Therefore, from a macroscopic meteorological perspective, temperature, humidity, and wind speed are the main meteorological factors that affect icing. Additionally, water bodies, windward/leeward slopes, and ridges affect icing thickness on transmission lines by influencing temperature, wind speed, water vapor, and other related meteorological factors.

1) Weighted Regression of Multiple Meteorological Factors

According to the Makkonen model, which was considered to reflect the key factors of icing thickness and meteorological environment well, the relationship between icing thickness and temperature, wind speed, and water vapor has been revealed. A regression model is established among them as follows:

$$Y = X\beta + \varepsilon \tag{2}$$

Where $Y = [y_1, y_2, \cdots y_n]^T$, $y_i (i = 1, n)$ represents the icing thickness at different time steps, and n is the time index. The variables X in the model are represented by different terms (Equation 3), where $x_{i,1}$ represents the square of wind speed, $x_{i,2}$ is the viscosity parameter (obtained from Equation 4), $x_{i,3}$ is the temperature, and $x_{i,4}$ is the relative humidity. To further consider the influence of temperature on icing thickness, the dew point temperature $x_{i,5}$ is introduced as an additional variable in the study to participate in icing thickness prediction.

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{3}$$

$$\begin{cases} \alpha_2 = \dfrac{1}{v}, v \ge 1m/s \\ \alpha_2 = 1, v < 1m/s \end{cases} \tag{4}$$

In the solution process, the coefficients β are obtained using weighted least squares, which effectively eliminates the influence of outlier data [10]. The specific solution is shown in Equation (5), where the equation is set to minimize the residuals:

$$\frac{\partial Q}{\partial \beta}=\frac{\partial \sum_i \varepsilon_i^2}{\partial \beta}=\frac{\partial (Y-\beta X)^T (Y-\beta X)}{\partial \beta} \\ =-Y^T X+X^T \beta^T X=0 \tag{5}$$

Thus, $\beta=\left(X^T X\right)^{-1} X^T Y, \varepsilon=Y-\beta X$.

Considering that each time step in the regression is equally weighted, the actual icing monitoring data have significant uncertainty due to the use of electronic instruments for automatic data collection. Therefore, the influence of extreme values and outliers needs to be considered. Weighted least squares can effectively handle outliers in regression analysis by assigning weights to each time step. $\omega_i=1/\varepsilon_i^2$. Equation (5) is then rewritten as:

$$\frac{\partial Q}{\partial \beta}=\frac{\partial \sum_i \omega_i \varepsilon'^2_i}{\partial \beta}=\frac{\partial (Y-\beta X)^T \mathrm{W} (Y-\beta X)}{\partial \beta} \\ =-Y^T WX+X^T \beta^T WX=0 \tag{6}$$

to obtain the coefficients $\beta=\left(X^T WX\right)^{-1} X^T WY$ and covariance $\sigma^2=\left(X^T WX\right)^{-1}$.

In practical prediction, NWP (numerical model prediction) data are used as the independent variables. The obtained parameters are assumed to be consistent with the monitoring point and remain unchanged in the near future, allowing for iterative predictions in the subsequent process. The prediction results using this method are denoted as Prediction 1 (P1).

2) Forecast method based on Makkonen model

In the Makkonen model, the product of the viscosity parameter, temperature, and relative humidity is directly proportional to the icing thickness. Therefore, the following prediction model is established:

$$y_{i,j}=\prod_{j=1}^{m} x_{i,j} \tag{7}$$

The independent variables $x_{i,j}$ remain the same as mentioned earlier. The prediction results using this model are denoted as Prediction 2 (P2).

3) Adjusted by AVT method

Based on the previous prediction results, the AVT (Average, Variance, Trend) technique is employed to further eliminate prediction biases. This method is considered effective in bias elimination [11]. Let's y_r、y_s denote the observed values as O and the predicted values as P. The following steps are performed using Equation (8) to remove trends from the observed and predicted data:

$$\begin{cases} y'_r=y_r-i\cdot h_r \\ y'_s=y_r-i\cdot h_r \end{cases} \tag{8}$$

Here, h_r、h_s represent the trends of the observed and predicted data, respectively. The trend for each sequence is calculated using the least squares method, resulting in detrended sequences, denoted as O' and P', respectively.

Next, the mean and variance of the detrended sequences are computed, and Equation (9) is used to correct the variance and mean of the detrended predicted data, resulting in corrected prediction sequences y''_s with the same mean and variance as the observed sequences. In Equation (9), a、σ represent the mean and variance of the observed sequence, while μ_P' and σ_P' represent the mean and variance of the detrended predicted sequence.

$$y''_s=\left(y'_s-a_{y'_s}+a_{y'_r}\right)\frac{\sigma_{y'_r}}{\sigma_{y's}}+i\cdot h_r \tag{9}$$

During actual prediction, the observed values are unknown. Therefore, historical data can be used to determine these parameters and iterate them into new prediction results to achieve icing thickness prediction.

III. RESULT

In practical prediction, the meteorological variables of air temperature, wind speed, and water vapor predicted by NWP are used to establish the relationship with the monitored ice accretion thickness. Two methods are employed to create functions for predicting ice thickness, followed by the application of the AVT (Adaptive Variance Transformation) method to correct the prediction results, resulting in the final predicted values. Since the prediction models are based on the numerical prediction of meteorological variables, separate models can be developed for each monitoring point, and the model parameters can be iterated in the subsequent processes to enable continuous ice accretion thickness prediction. The predicted ice thicknesses using the two methods are denoted as P1 and P2, respectively.

A. Prediction on a single station

For the four-day ice accretion process from January 8th to January 11th, 2021, two prediction methods were applied to study the ice accretion thickness. Figure 1 shows the ice accretion prediction results for monitoring point (103.8490, 27.8857), with ice thickness values of 3.1mm, 3.4mm, 3.4mm, and 4.1mm for the respective days. It can be observed that the ice thickness gradually increases over time. Prediction method 1 (P1) yields ice thickness values of 2.9mm, 3.6mm, 3.6mm, and 3.9mm, with a deviation of 0.2mm from the observed values. Prediction method 2 (P2) produces ice thickness values of 3.2mm, 3.3mm, 3.5mm, and 4.2mm, with a deviation of 0.25mm from the observed values. The prediction errors for methods 1 and 2 are 5.77% and 2.89%, respectively.

Figure 2 presents the ice monitoring and prediction results for another monitoring point. It can be observed that the ice thickness at this point is comparable to that of the first monitoring point. However, there are still deviations between the predicted and observed values. The observed ice thickness values for the four days are 3.7mm, 4.7mm, 4.7mm, and 3.3mm. Prediction values for P1 are 3.7mm, 4.6mm, 4.8mm, and 3.3mm, while for P2, the values are 4.8mm, 3.8mm, 3.3mm, and 4.6mm. The deviations from the observed values are 0.1mm and 1.2mm for P1 and P2, respectively, with prediction errors of 1.06% and 29.51%. In summary, for relatively light ice accretion (less than 10mm), both methods exhibit small deviations in predicting ice thickness, typically around 1mm.

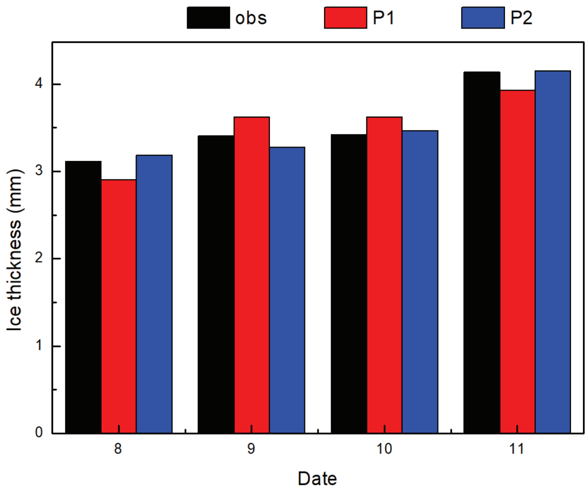

Figure 1. Observation and forecast result in station 1（Station: 103.85° E、27.89° N）

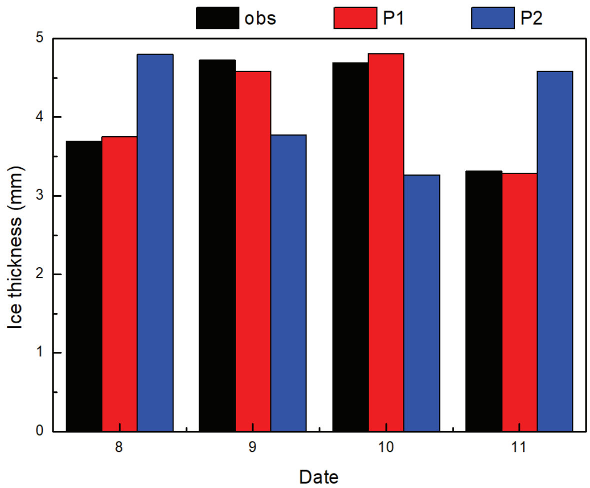

Figure 2. Observation and forecast result in station 2（Station: 103.70° E、27.49° N）

Comparing the prediction of ice accretion thickness in the range of 10-20mm, Figure 3 shows the ice accretion prediction results for monitoring point (103.8400, 27.4844) over a period of 4 days (8th to 11th). The observed ice thickness during this period was 19.8mm, 14.7mm, 8.8mm, and 12.1mm, showing a gradual decrease. Prediction method 1 yielded ice thickness values of 20.8mm, 12.1mm, 11.1mm, and 11.4mm, with a deviation of 1.7mm from the observations. Similarly, prediction method 2 produced ice thickness values of 20.8mm, 12.0mm, 11.2mm, and 11.4mm, also exhibiting a deviation of 1.7mm from the observations. The prediction deviations for the two methods were 13.66% and 14.12%, respectively. Figure 4 illustrates the ice accretion thickness for another monitoring point, which shows good agreement with the observed data, but with a gradual increase in ice thickness. The observed ice thickness values were 9.6mm, 6.4mm, 9.7mm, and 15.9mm, while the predicted values using method 1 were 9.7mm, 5.7mm, 10.9mm, and 15.3mm, and using method 2 were 9.6mm, 6.1mm, 10.1mm, and 15.8mm. The deviations between the predictions and observations were 0.66mm and 0.23mm, with error rates of 7.03% and 2.36%, respectively. For medium ice thickness(10-20mm), the deviations in predictions from the two methods were around 1-2mm.

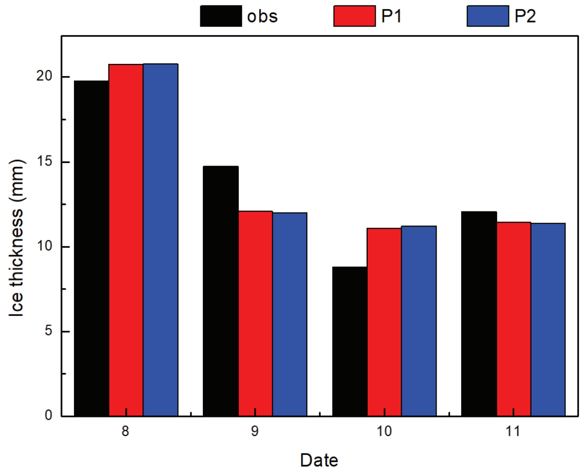

Figure 3. ce accretion observation and prediction results for monitoring point (103.84°E, 27.48°N).

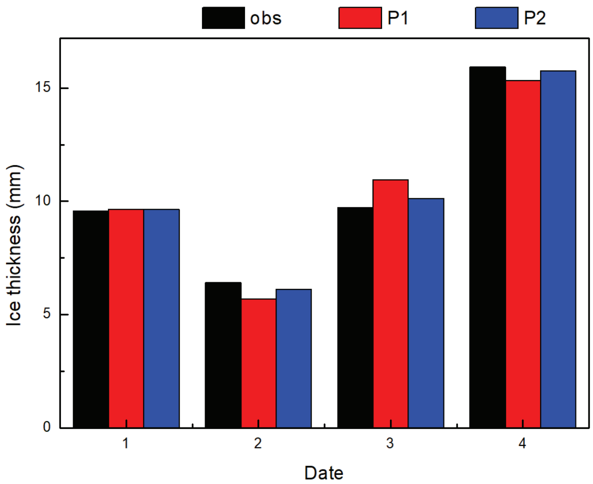

Figure 4. Ice accretion observation and prediction results for monitoring point (103.69°E, 27.49°N).

Further analysis was conducted for ice accretion exceeding 20mm. Figure 5 presents the predicted ice thickness using different prediction techniques, focusing on monitoring point (101.01°E, 27.17°N). The observed ice thickness values were 34.7mm, 33.6mm, 34.2mm, and 32.6mm, which nearly reached the maximum ice thickness (40mm) during this period. The predictions from method 1 were 34.4mm, 34.2mm, 34.2mm, and 32.4mm, while method 2 yielded predictions of 34.2mm, 34.8mm, 33.5mm, and 32.7mm, which were in close agreement with the observations. The deviations between the predictions and observations were 0.3mm and 0.6mm, with prediction error rates of only 0.82% and 1.84%, respectively. Overall, the prediction results for the ice accretion thickness at this monitoring point were satisfactory, possibly due to the relatively stable ice thickness during this period.

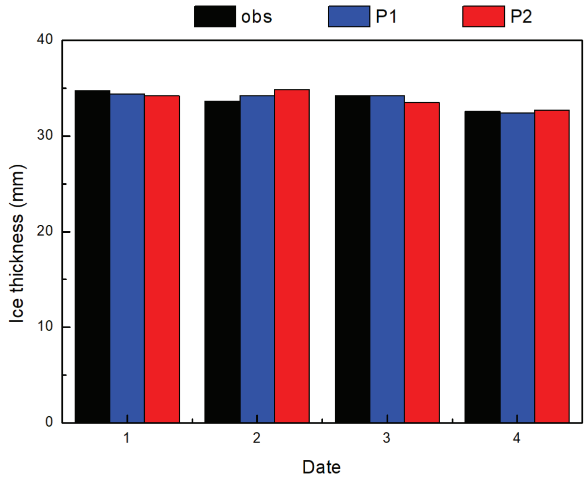

Figure 5. Ice accretion observation and prediction results for monitoring point (101.01° E、27.17° N).

B. *Prediction on multiple stations*

Comparing the ice accretion thickness predictions for different monitoring points at various ice thickness levels, it can be observed that both methods exhibit small deviations in the predicted ice thickness, ranging from 1-2mm. This indicates that the methods possess a certain level of predictive capability. Further analysis was conducted on the ice accretion thickness predictions for 238 monitoring points with available data during this ice accretion process (Figure 6, January 8th). It can be seen that the majority of monitoring points had their ice thickness accurately predicted by both methods (upper plot). Looking at the prediction deviations (lower plot), for method 1, the ice thickness prediction deviations were less than 1mm for the majority of monitoring points (84.45%), with only 3 monitoring points exceeding a deviation of 5mm. For method 2, 59.66% of monitoring points had ice thickness prediction deviations less than 1mm, 35.71% had deviations between 1-2mm, and 11 monitoring points had deviations exceeding 5mm. On average, method 1 had an average prediction deviation of 0.6mm, while method 2 had an average deviation of 1.5mm for the ice accretion thickness.

Overall, the average prediction bias for ice thickness using method 1 is 0.6mm, while for method 2 it is 1.5mm. Therefore, method 1 shows relatively better predictive performance across different monitoring points. It should be noted that these results are based on data from January 8th, and the specific monitoring points and bias patterns may vary due to temporal and spatial changes.

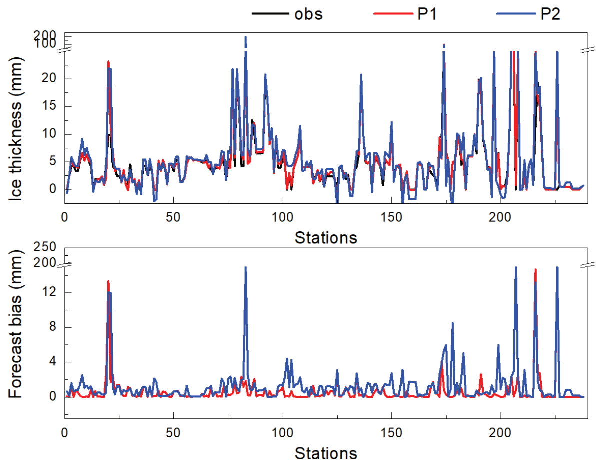

Figure 6. Forecast bias of different monitor stations(Jan. 8th)

Analysis of the forecasting performance under different icing thicknesses (Table 2) reveals that for very light icing with thicknesses less than 5mm, Method 1 achieves an average prediction deviation of 0.43mm, while Method 2 has an average deviation of 1.20mm. For light icing with thicknesses ranging from 5mm to 10mm, Method 1 yields an average deviation of 0.67mm, whereas Method 2 has an average deviation of 1.84mm. In the case of severe icing with thicknesses between 10mm and 20mm, Method 1 exhibits a prediction deviation of 1.38mm, compared to Method 2 with a deviation of 1.84mm. When the icing severity reaches the level of heavy icing (thickness exceeding 20mm), Method 1 shows a deviation of 3.37mm, while Method 2 has a deviation of 5.34mm.

Overall, Method 1 outperforms Method 2 in terms of prediction deviation. Specifically, Method 1 achieves an average deviation of approximately 0.5mm for icing thicknesses below 20mm, and around 2-3mm for icing thicknesses exceeding 20mm. Method 2 exhibits a deviation in the range of 2-3mm, which increases for thicker icing layers.

TABLE II. AVERAGE PREDICTION BIASES FOR THE TWO METHODS AT DIFFERENT ICE THICKNESS LEVELS

	Ice thickness (h, mm)	*Prediction biases of P1(mm)*	*Prediction biases of P2(mm)*
Very light ice	0⩽h<5	0.43	1.20
Light ice	5⩽h<10	0.67	1.55
Medium ice	10⩽h<20	2.38	1.84
Heavy ice	20⩽h	3.37	5.34

IV. DISCUSSION

In this study, the Weather Research and Forecasting (WRF) model is employed to predict weather conditions during the icing period and determine the formation of icing conditions. The Makkonen model, recommended by the International Electrotechnical Commission (ISO 12494-2017), is then used to identify the main meteorological factors influencing the icing process, including temperature, humidity, and wind speed. These meteorological elements are extracted from the numerical model's predictions. We proposes an overhead power line icing prediction method based on weighted regression using multiple meteorological factors. The method utilizes NWP to predict meteorological elements in the area where ice accretion occurs and employs statistical methods to construct prediction models. Finally, two icing thickness prediction models are constructed based on the predicted meteorological factors and observed icing thickness data. The research focuses on icing thickness prediction in the Yunnan region.

The results indicate the following:

- Both prediction models, Model 1 constructed using weighted least squares regression and Model 2 utilizing the Makkonen model directly, accurately predict the icing process. Around 80% of the monitoring points exhibit consistent icing thickness predictions within a deviation range of approximately 1-2mm compared to the observed values.
- Considering the icing thickness predictions from all 238 monitoring points, Model 1 shows significantly smaller average prediction biases than Model 2. The former has an average prediction bias of around 0.5mm, while the latter reaches approximately 1mm (even up to 1.83mm for icing thickness less than 1mm).

However, we acknowledge that both predition models may have limitations due to the shortage of observational data. Yet this still exhibit the potential to forecast overhead transmission line icing to some extent. With the extensive utilization of observational data, this method can be further optimized to enhance forecasting accuracy.

Acknowledgment

We thank the funding agency for supporting our research project (Project No. 2022GK2052), and all individuals who contributed.

We acknowledge the valuable input and feedback from our colleagues and peer reviewers. Their constructive criticism and suggestions helped improve the quality of our work.

References

[1] Huang X B, Liu J B, Cai W, et al. Present research situation of icing and snowing of overhead transmission lines in China and foreign countries. Power Sys Techno, 2008, 32(4):23-28

[2] Lu J Z, Jiang Z L, Lei H C, et al. Analysis of Hunan power grid ice disaster accident in 2008. Automat Electron Power Sys, 2008, 32(11):16-19.J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[3] Yang J, Xie Z Z. Advances of study on physical process and modeling of ice accretion on wires. Meteor Mon. 2011,37(9):1158-1165

[4] Jones K F. A simple model for freezing rain ice loads. Atmos Res, 1998, 46(1):87-97.

[5] Makkonen L. Modeling of ice accretion on wires. J Climate Appl Meteor, 1984, 23(6):929-939.

[6] Makkonen L. Modeling power line icing in freezing precipitation. Atmos Res, 1998, 46(1/2): 131-142.

[7] Liao Y F, Duan L J. Study on estimation model of wire icing thickness in Hunan Province. Trans Atmos Sci, 2010, 33(4):395-400.

[8] Song D, Xia X L, Zhang L,et al. Guizhou wire icing thickness forecast method based on stepwise regression and discriminant analysis. J Meteor Res Appl, 2018, 39(4): 26-29.

[9] Dai D, Huang X T, Dai Z, et al. Regression model for transmission lines icing based on support vector machine. High Voltage Engineering, 2013, 39(11):2822-2828.

[10] Yan PC, Hou W, Qian ZH, He WPm Sun JA. The analysis of the influence of globe SST anomalies on 500 hPa temperature field based on Bayesian. Acta Phys. Sin., 2012, 61(13): 139202.

[11] Zhang Tiejun, Yan Pengcheng*, Li Zhaorong, et al. Bias-correction method for wind-speed forecasting. Meteorol. Z. 2019, 28(4): 293-304. DOI 10.1127/metz/2019/0950