Short-term ice accretion forecasting model for transmission lines with modified time-series analysis by fireworks algorithm

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Abstract: In order to reduce the damages of transmission line icing, an effective ice accretion forecasting can be used to guide the de-icing work. The ice accretion on transmission lines varies slowly over time, and the icing data series is characteristic of timing sequence and autocorrelation. Time-series analysis is suitable for analysing the similar data series, and fireworks algorithm (FA) is used to determine the autoregressive order and the moving average order of time-series analysis. Then a short-term ice accretion forecasting for transmission lines with modified time-series analysis by FA is built. The ice accretion experiments were done in artificial icing laboratory. The results show that the modified time-series analysis model by the FA has higher accuracy than another five models, whose relative errors are <1.3% and closer to the experimental data. Field applications also show that the modified time-series analysis model has higher accuracy than the traditional one for the short-term ice accretion forecasting, whose average error rates are separately 2.6723 and 5.2654%.

1 Introduction

Atmospheric icing affects a wide variety of transmission lines in many countries, and there are thousands of transmission line failures worldwide caused by excessive ice loading each year. Utilities have to spend millions even billions of dollars on restoration efforts. The images in Fig. 1 show the damages caused by icing overload on transmission lines in Lishui area, Zhejiang province, China.

After 2008, many techniques developed by both State Grid and South Grid in China were used to decrease or eliminate the catastrophic damages due to the continuous icing, which included methods of icing measuring, icing melting, anti-icing etc. The short-term forecasting of ice accretion on transmission lines can help electric power companies and communities to get prepared and take appropriate preventive measures. How to develop the ice accretion forecasting methods is an interesting research. Many analytical, experimental, and field studies have been carried out to improve the understanding of various ice accretion processes, which emphasise the ice accretion, the ice flashing, and the design of transmission lines subjected to ice loads etc. However, the ice accretion is not only related to the various meteorological parameters, but also influenced by the construction and operation of transmission lines. It is much clearer to utilise numerical models to describe its process, rather than observations and measurements alone [1]. The numerical icing models can be separated into the physical icing models and the purely statistical icing models. Usually, the physical icing models are based on fluid mechanics and thermodynamics etc., whose key parameters involve liquid water content (LWC), median volume diameter (MVD), meteorological parameters (especially air temperature, wind speed), surface roughness of the ice or conductor, ice density, thermal parameters (such as heat transfer coefficient, icing thermal conductivity) etc. [1, 2]. The icing shape, the icing density, and the icing mass are predicted by analysing the process of ice accretion. The Makkonen model, the Imai model, the Goodwin model etc. are well known and widely used [3–5]. In 2015, Dimitar Nikolov used the observation data of Bulgaria for 30 years to verify six wet snow accretion models which involves the model of Admirat and Sakamoto [6–8], the model of Finstad et al. [9], the model of Sakamoto and Miura [10], the model of Makkonen [11] and its improvement [12], and the model of Nygaard et al. [13]. The results show that each model has advantages, disadvantages, and different predicting accuracy in different conditions [14]. Although most physical models are created theoretically, some empiricism must be still included in the modelling process due to lack of the necessary input data for the icing models [1]. These empirical parameters or methods are usually derived or analysed by statistics.

The purely statistical icing models can build relationship between the ice accretion and the meteorological factors (temperature, humidity, wind speed etc.). From a statistical point of view, the further ice accretion can be forecasted by those models. Based on theoretical simulation and field observation, Zavarina and Sundin built the early empirical and statistical approaches, which are still valid in predicting the cumulative ice loads [15, 16]. With the development of computers and information processing, many complex, non-linear, and intelligent methods are used to build the icing models. Particularly, there are many advanced ice accretion models applied to airplane ice accretion forecasting, where both subjective and objective parameters are analysed in ice accretion.

Fig. 1 Damages of transmission line icing in Zhejiang province in 2008
(a) Collapse of tower, (b) Fracture of tower head, (c) Failure of ground wire, (d) Fracture of conductor
rigorously [17]. Those ice accretion models for airplanes can also be used for forecasting the ice accretion on transmission lines. The intelligent algorithms were used to extract micrometeorology features and assess the icing status of transmission lines [18]. A numerical weather prediction is applied to an ice accretion forecasting system for power transmission lines [19]. The modified hidden semi-Markov model was built to predict the remaining dangerous time for icing load accretion on an interval of the power transmission lines [20]. The fuzzy logic theory and relevant improvement algorithms [21], the fuzzy Markov chain prediction [22], the support vector regression learning algorithm [23], and the wavelet support vector machine based on a quantum fireworks optimisation algorithm [24] were used to build the icing thickness prediction models. The ice accretion forecasting models based on backpropagation (BP) neural network are widely used, by which the relationship between the input parameters and the icing rate can be built effectively [25, 26]. However, the BP neural network is usually easy to get the local optimum, whose network structure is difficult to determine and generalisation ability is poor. Then some ice accretion forecasting models are newly built based on the improved BP neural network. A Takagi–Sugeno fuzzy neural network was proposed to predict the icing thickness under extreme cold weather conditions [27]. The genetic algorithm (GA) was used to optimise the convergence ability of the BP neural network and improves the prediction accuracy [28]. The appropriate input parameters of BP neural network need to be selected to guarantee the time validity and accuracy, which cannot be selected well yet now.

The purely statistical ice accretion models must be built on the available ice accretion data which is from theoretical simulation and field observation. The icing data must be measured in chronological order and recorded with all key parameters, which are related to meteorology, conductors, and even topography. The ice accretion data is measured by real-time instruments, and each set of ice accretion data should include all influential factors as possible.

The ice accretion on transmission lines varies slowly over time, and the icing data series is characteristic of timing sequence and autocorrelation. Time-series analysis is suitable for analysing the similar data series, but the time-series analysis’ order determination is uncertain and it will influence the forecasting precision of the model. Compared with GA and PSO which need more parameters and show the slow convergence [29, 30], the fireworks algorithm (FA) is used to quickly optimise the autoregressive order \( p \) and the moving average order \( q \). The semi-elite selection mechanism for the position of the fireworks and its explosive sparks is used to determine the positions of the offspring explosion, by which the elite information and the diversity are reserved and the precocious probability decreases. Then the short-term ice accretion forecasting model on transmission lines based on time-series analysis improved by FA is presented in this paper.

2 Forecast the short-term ice accretion for transmission lines with modified time-series analysis by FA

A short-term ice accretion forecasting model for transmission lines with modified time-series analysis by FA is built based on the timing sequence relationship of the ice accretion data series, which is indeed a mathematical fitting statistical method. The ice accretion on transmission lines varies slowly over time, and the icing data series is characteristic of timing sequence and autocorrelation. Time-series analysis is suitable for analysing the ice accretion, where the order determination is very important.

2.1 Time-series analysis model

As for the icing process of transmission lines, \( X(t) \) is defined as the ice mass at time \( t \). \( X(t) \) is not only related to the ice mass before time \( t \), but also partly influenced by the ice accretion perturbation. Then the abstract system of the ice accretion process is called an autoregressive integrated moving average system, whose mathematical definition is marked as ARIMA\((p, d, q)\) [31].

For a stable data series, \( X(t) \) can be expressed by

\[
X(t) = \phi_1 X(t-1) + \cdots + \phi_p X(t-p) + \theta_1 \varepsilon(t-1) + \cdots + \theta_q \varepsilon(t-q) + \varepsilon(t),
\]

where \( \phi_p \) is the autoregressive coefficient; \( \theta_q \) the moving average coefficient; \( \varepsilon(t) \) the white noise time series; \( p \) and \( q \) separately represent the autoregressive order and the moving average order, and \( d \) represents the difference order of time series, \( d \) is set to 0.

For an unstable data series, the data series must be differentiated \( d \) times. In most cases, \( d \) should be 1 or 2. \( X(t) \) can also be expressed by (1).

Determination of \( p \) and \( q \) is called the order determination, and there are many available methods. The autocorrelation function and partial correlation function can be used only for the AR model. Schwartz principles (SC) and Akaike information criterion (AIC) can be used for the ARMA model, AR model, and MA model, but the obtained order is usually the local minimum which is not the best without repeated comparison [32]. FA is a different optimisation method, which is feasible to quickly optimise the autoregressive order \( p \) and the moving average order \( q \) [33].

2.2 FA for the order determination

The FA is good at finding the global optimal solution, whose search mechanism is as follows [33].

Firstly, randomly set \( N \) explosive positions of the fireworks as the original solution, and the position of explosive \( i \) can be expressed as \( x_i = (x_{i1}, x_{i2}) \), where \( p = 1 \) and \( q = 1 \).

Secondly, set the biggest explosive radius \( r_{max} \) for all the explosive positions sparkles which means the spark's biggest scattered areas, and it could linearly decrease with generation \( n \), which is shown below:

\[
r_{max} = \frac{T-n}{T}(r_{initial} - r_{end}) + r_{end}
\]

Thirdly, explode the explosives we set above, and its sparkle positions will be determined by:

\[
\begin{align*}
x'_j &= x_i + r_{j1} \vec{b}_j, \\
r_{j1} &= jr_{j1}/w \quad (j = 1, 2, \ldots, w)
\end{align*}
\]

where \( r_{initial} \) and \( r_{end} \) separately represent the biggest explosive radius of the first explosive and the last explosive; \( T \) is the biggest iteration number of the algorithm; \( x_i \) the current position of explosive \( i \) and \( x'_j \) is its sparkle position; \( \vec{b}_j \) the direction vector of explosion; \( r_{j1} \) the explosive radius of the layer \( j \) which is set from 1 to \( w \), the largest explosive layers.

The direction vector of explosion is displayed in the standard 2D coordinates, as shown in Fig. 2.

Finally, calculate the optimal \( p \) and \( q \) by the armax function in MATLAB. The fitness function is used to judge the effectiveness of \( p \) and \( q \), which is shown below:

\[
J = \sum |y_i - X_i|
\]
2.3 Short-term ice accretion forecasting model based on time-series analysis improved by the FA

The FA is used for the order determination of time-series analysis, then the short-term ice accretion forecasting model for transmission lines with modified time-series analysis by FA is built in details as follows:

Step 1: Stabilise the ice accretion data series. The autocorrelation coefficient of data series can be used to judge the stability of data series. If it cannot quickly converge to zero, the data series is unstable and must be differerntiated. After one or two or more order difference, the differerntiated data series whose autocorrelation coefficient can quickly converge to zero is stable, and we make the $d$ represents the difference order of data series.

Step 2: Set parameters $T$, $r_{\text{initial}}$, $r_{\text{end}}$ and $w$. Based on the complexity of the problem, the requirements of performance and the available research of similar problems, the parameters are initially set and also modified, which are proved effective in forecasting short-term ice accretion. Then in this model, we set $T = 100$, $r_{\text{initial}} = 5$, $r_{\text{end}} = 10^{-w}$, and $w = 3$.

Step 3: Randomly set $N = 20$ explosive original positions of the fireworks in the standard 2D coordinates, and set $t = 1$.

Step 4: Calculate the maximum radius $r_i$ in the iteration process by (2).

Step 5: Explode the fireworks whose sparkles are generated by (3).

Step 6: Substitute $p$ and $q$ with the sparkle positions, and the fitness value will be calculated by every $p$ and $q$ according to (4), then the optimal $N/2$ sparkles will be selected and the rest $N/2$ sparkles can be selected randomly in the rest sparkles. The new $N$ sparkles consisting of the separate $N/2$ sparkles above will be kept for the next generation, and the other sparkles will be discarded. Meanwhile, set $n = n + 1$.

Step 7: If $n < T$, return to step 3. Otherwise, output the best $p$ and $q$, then ARIMA($p$, $d$, $q$) can be built.

3 Experiments of forecasting short-term ice accretion

The experiments of forecasting conductor ice accretion were done in an artificial icing laboratory, by which the icing forecasting model can be validated.

3.1 The artificial icing laboratory

The artificial icing laboratory consists of artificial climate chamber, transformer, simulation conductor, refrigeration compressor, insulator string, casing, auto spray device, adjustable fan etc., as shown in Fig. 3. Two refrigeration compressors with the capacity of 2.5 and 8.0 kW are available, by which the desirable ambient temperature within $-25$ to $0^\circ$C can be generated as planned. A group of blowers are placed in the rear part of the chamber and connected to the power system through variable-frequency devices, by which the constant wind velocity in the range of 0–12 m/s can be generated. The auto spray device consists of the compressor, air filter, water filter, pressure regulator, and seven nozzles, which is employed to adjust the parameters of droplets such as LWC and MVD. Both the ice accretion and the ice melting experiments can be done in this laboratory, the process of which can also be observed and measured digitally.

3.2 Experiments of the conductor ice accretion

An aluminium cable steel reinforced whose diameter is 21.6 mm is selected as a simulation conductor. The ice such as glaze ice and rime ice etc. can grow on the conductor, by controlling the ambient temperature, the wind speed, the droplets with different LWC, and MVD. The total icing time is 14 h which began at 7 : 00 and ended at 21 : 00, and the icing thickness measurements of the ice accretion are done automatically every half an hour. The ice accretion condition is also changed each hour to simulate the varied meteorological parameters in a natural environment. In the experiments, an online monitoring instrument is especially developed to measure the weight of the iced conductor by two force sensors, by which the icing process can be measured without any interruption on the accretion caused by the measurement behaviours. The icing mass per metre can be gotten by subtracting the equivalent icing thickness can also be calculated [34]. For the online monitoring system of transmission lines icing, we use the ‘three tower two span’ mechanical model to get the equivalent icing thickness. Twenty-nine groups of icing data can be taken in a 14 h icing experiment, as shown in Table 1, the first 20 groups of which are used for training data, the subsequent 5 for validating data, and the last 9 for forecasting data.

3.3 Accuracy of forecasting ice short-term accretion

(i) Stabilise the ice accretion data series: The autocorrelation coefficient of data series as shown in Fig. 4a can be used to judge its stability.

Since the autocorrelation coefficient of the ice accretion data series as shown in Fig. 4b cannot quickly converge to zero, the data series is unstable.

Then this data series must be differentiated as shown in Fig. 4c. After one order difference, the differentiated data series is shown in Fig. 4d, whose autocorrelation coefficient can quickly converge to zero. We can find the differentiated data series after one order difference is stable, then $d$ is set to 1.

(ii) Short-term ice accretion forecasting model for transmission lines with modified time-series analysis by FA: By the FA above,
the optimal \( p \) and \( q \) are calculated as 3 and 0 separately, then we can use ARIMA(3, 1, 0):

\[
X(t) - 0.8510X(t-1) - 0.0723X(t-2) - 0.0056X(t-3) = \varepsilon(t) \\
\] (6)

For analysing the effect of different order determination methods in time-series analysis model, we illustrate AIC to realise the order determination and the time-series analysis model is the ARIMA (2,1,1):

\[
X(t) - 0.9423X(t-1) - 0.0403X(t-2) = \varepsilon(t) - 0.233\varepsilon(t-1) \\
\] (7)

**Table 1**  Icing data in a 14 h icing experiment

| Time   | Temperature, °C | Wind speed, m/s | Precipitation intensity, mm/12 h | Icing thickness, mm |
|--------|-----------------|-----------------|-----------------------------------|---------------------|
| 7:00   | −5              | 1               | 24                                | 0.0000              |
| 7:30   | −5              | 1               | 24                                | 13.1002             |
| 8:00   | −2              | 2               | 24                                | 32.2204             |
| 8:30   | −2              | 2               | 24                                | 43.3142             |
| 9:00   | 2               | 5               | 12                                | 51.3253             |
| 9:30   | 2               | 5               | 12                                | 51.0225             |
| 10:00  | 4               | 7               | 12                                | 49.7201             |
| 10:30  | 4               | 7               | 12                                | 47.8001             |
| 11:00  | −3              | 3               | 12                                | 46.8847             |
| 11:30  | −3              | 3               | 12                                | 50.4342             |
| 12:00  | −5              | 5               | 24                                | 56.5859             |
| 12:30  | −5              | 5               | 24                                | 60.8214             |
| 13:00  | −7              | 4               | 18                                | 65.2045             |
| 13:30  | −7              | 4               | 18                                | 67.0784             |
| 14:00  | 1               | 2               | 18                                | 68.0057             |
| 14:30  | 1               | 2               | 18                                | 69.2247             |
| 15:00  | 0               | 2               | 12                                | 68.5045             |
| 15:30  | 0               | 2               | 12                                | 67.8657             |
| 16:00  | −1              | 5               | 12                                | 67.6346             |
| 16:30  | −1              | 5               | 12                                | 67.3527             |
| 17:00  | 3               | 1               | 12                                | 67.0225             |
| 17:30  | 3               | 1               | 12                                | 66.0354             |
| 18:00  | 2               | 4               | 24                                | 65.0038             |
| 18:30  | 2               | 4               | 24                                | 64.2102             |
| 19:00  | −4              | 6               | 12                                | 63.7248             |
| 19:30  | −4              | 6               | 12                                | 64.5159             |
| 20:00  | −5              | 8               | 18                                | 65.8273             |
| 20:30  | −5              | 8               | 18                                | 66.8335             |
| 21:00  | −5              | 8               | 18                                | 68.2451             |

**Fig. 4**  Data series with one order difference

(a) Original icing data series,  (b) Autocorrelation coefficients of the first 20 data groups,  (c) Data groups after one order difference,  (d) Autocorrelation coefficients of the first 20 data groups after one order difference
The short-term ice accretion forecasting results with two order determination methods are shown in Fig. 5. As seen from Fig. 5, compared with the short-term ice accretion forecasting model based on traditional time-series analysis, the short-term ice accretion forecasting model for transmission lines with modified time-series analysis by FA has higher accuracy, whose relative errors from 17 : 00 to 19 : 00 are <1.3% and closer to the experimental data.

4 Contrastive analysis with other short-term ice accretion forecasting models

As mentioned in Section 1, Makkonen model, BP neural network model etc. have been widely applied and effectively validated. Then we compare the forecasting results of the model with modified time-series analysis by FA with that of other five models, e.g. the model of Makkonen [3], the model of SVM [25], the model of BP neural network [18], the model of fuzzy logical [20], and the traditional time-series model [31]. For the same experimental data, the forecasting results are shown in Table 2 and Fig. 6.

As seen in Fig. 6, the accuracy of traditional time-series model is lower than that of modified time-series analysis model by FA. The statistical icing models (BP neural network, fuzzy logical, and time-series model) are superior to the physical icing model (Makkonen model) in the short term (from 17 : 00 to 18 : 30), and the accuracy of modified time-series analysis model by FA is the highest. The average error rates of different models are separately 0.3823% (model in this paper), 0.9467% (traditional time series), 0.8965% (fuzzy logic), 0.7865% (BP neural network), 0.6017% (SVM), and 2.1598% (Makkonen). However, for long-term forecasting (from 19 : 00 to 20 : 00), the physical icing model has a better adaptability and accuracy than the statistical icing models. The average error rates of different models separately are 1.5826% (model in this paper), 3.3099% (traditional time series), 2.3463% (fuzzy logic), 1.7871% (BP neural network), 1.181% (SVM), and 1.5499% (Makkonen).

5 Field application of the short-term ice accretion forecasting model for transmission lines with modified time-series analysis by FA

Table 2

| Time   | Experimental data, Makkonen, mm | BP neural network, mm | SVM, mm | Fuzzy logic, mm | Traditional time series, mm | Model in this paper, mm |
|--------|--------------------------------|-----------------------|---------|-----------------|----------------------------|------------------------|
| 17 : 00 | 67.2025                         | 67.2002               | 67.1135 | 67.1052         | 67.1088                    | 67.1034                |
| 17 : 30 | 66.0354                         | 66.3245               | 66.7854 | 66.6532         | 66.6548                    | 66.1228                |
| 18 : 00 | 65.0038                         | 65.0042               | 65.8932 | 65.7632         | 65.8567                    | 66.0042                |
| 18 : 30 | 64.2102                         | 66.3579               | 64.5355 | 64.3256         | 64.9584                    | 64.5104                |
| 19 : 00 | 63.7248                         | 64.2758               | 63.4043 | 63.2438         | 62.1018                    | 62.0213                |
| 19 : 30 | 64.6159                         | 65.5287               | 63.5416 | 63.6794         | 62.2476                    | 62.2157                |
| 20 : 00 | 65.8273                         | 66.5461               | 64.6201 | 64.7753         | 64.7054                    | 63.2338                |
| 20 : 30 | 66.8335                         | 68.0205               | 65.5140 | 65.5762         | 65.2465                    | 64.5021                |
| 21 : 00 | 68.2451                         | 70.0224               | 66.2238 | 66.5127         | 66.2057                    | 66.4105                |
| Average error rate | 1.821%                     | 1.3424%                | 1.181% | 1.7019%          | 2.2545%                     | 1.0819%                |

Fig. 5 Short-term ice accretion forecasting results of model based on time-series analysis with both different order determination methods

Fig. 6 Comparison of the forecasting results of six different models (a) Forecasting results of six different models, (b) Absolute errors (AE) of six different models, (c) Errors (E) for the total amount of ice in each of the different short-term ice accretion forecasting models

5.1 Icing online monitoring system

An icing online monitoring system of transmission lines was developed [34], by which the ice accretion process can be measured remotely. The system developed before consists of four parts which are the provincial monitoring centre host, the urban monitoring centre host, the online monitoring station, and the expert software, whose schematic diagram is shown in Fig. 7a. The online monitoring station installed on towers, as shown in Fig. 7b, consists of main control unit (MCU), sensors, power unit, and communication unit. Both ARM and DSP act as MCU. The icing data series consisting of the environmental temperature, humidity, wind speed, wind direction, rainfall, and icing thickness can be measured by various sensors, which can be sent to the urban monitoring centre by GPRS/3G/4G/OPGW communication methods. The urban monitoring centre where the expert software is installed can communicate with many online monitoring stations installed on towers at the same time.

The system has been installed in Shaanxi province, Guizhou province, and other areas subjected to icing. Many icing accidents...
are recorded successfully, as shown in Fig. 7b, and the icing data series consisting of environmental temperature, humidity, wind speed, wind direction, rainfall, icing thickness etc. can be used to validate the icing forecasting models.

### 5.2 Icing forecasting and analysis

Many icing accidents are recorded by the icing online monitoring system, the icing data of which can also be used to validate the ice accretion forecasting models. For example, there was an icing accident which occurred in December 2011 on 220 kV Kaiyu line in the Guizhou power grid. One icing data group can be taken every 15 min, which the icing data series for 10 days has 960 groups, as shown in Fig. 8.

The results of the traditional time-series analysis model and that of the modified time-series analysis model by FA are compared in Fig. 9. For the short-term forecasting (from 10th to 15th day), the modified time-series analysis model has higher accuracy than the traditional one, whose average error rates are separately 2.6723 and 5.2654%. Owing to the accumulation of error, the modified time-series analysis model can only forecast the general trend of ice accretion after the 15th day. However, the traditional one has lost its reference value. The ice forecasting model should be reliable when the time interval is between 3 and 5 days. So the modified time-series analysis model by FA is valuable in application.

### 6 Conclusion

A short-term ice accretion forecasting model for transmission lines with modified time-series analysis by FA is presented in this paper, which is superior to the traditional time-series analysis model and the other available ice accretion models issued before.

Most empirical models consider the accretion process to be static, which is appropriate for icing events of short to medium
duration. When the ice accretion data suffers a sudden change, the presented ice accretion forecasting model will lose its accuracy. Then we should consider the dynamics of the ice accretion [3, 35] and correct the modelling of long-term icing events. This task will be a part of our future research.

7 References

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