

# Application of ARMA Model in Prediction of Development Trend of Partial Discharge

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**Keywords:** Partial discharge, ARMA model, trend, prediction.

**Abstract:** Nowadays, gas insulated switchgear (GIS) has been widely used in power systems. Due to some external factors, there may be defects in GIS, and some minor defects are difficult to find in the early stage. However, partial discharges (PD) is easy to occur in the defects and make the defect large, which may cause the failure of GIS and bring about huge economic losses to both power systems and society eventually. Therefore, it is helpful to discover the defect discharge in time and predict its development trend for the early warning of fault and taking suitable countermeasures. In this paper, ARMA model is selected to predict the development trend of partial discharge, and partial discharge experiment and three kinds of defect models are designed evaluate the prediction effect of the ARMA model. Finally, the conclusion is drawn that ARMA model can accurately predict the development trend of linear characteristic parameters, but it cannot predict that of irregular characteristic parameters of PD accurately.

## 1 INTRODUCTION

Since the 1970s, gas insulated switchgear (GIS) has been widely used in power systems due to its high reliability and compact structure (Кучинский, 1984; Qiu, 1994; Bolin, 2005). Due to some mistakes in the process of production, transportation, assembly, etc., there may be typical defects which will lead to partial discharge (PD) such as the suspension discharge, corona discharge and the discharge of void inside the insulating material(Qi, Li, Hao, 2011; Liu, Wang, LI, 2013). Under long-term working conditions, partial discharge will cause insulation degradation, which will easily lead to GIS failure during operation, and affect the stable operation of the power system (Martin, Li, Tsutsumi, 2012; Pharmatrisanti, Meijer, Smit, 2004). In recent years, many GIS faults caused by PD at the position of insulation defects have been discovered, which has caused great losses to the power system (Ren, Dong, Qiu, 2017; Tang, Tang, Li, 2017; Zhou, Tang, Tang, 2006). Therefore, it is necessary to study the development of partial discharge generated by defects in GIS, and predict the development trend of PD, which helps to warn the occurrence of faults and

avoid serious losses(Strachan, McArthur, Judd, 2005; Li, Sun, Du 2002; Liu, Lv ,Li,2004; Qi, Li, Xing, 2014).

H. Okubo et al. used a breakdown prediction parameter which characterizes the change of PD to predict the time to breakdown (Okubo, Kato, Hayakawa, 1998). However, the mechanism of partial discharge are complicated and the phenomenon is always affected by various factors such as operating voltage and load of equipment, which makes the development of partial discharge nonlinearly and randomly. So, it is not rigorous to characterize the development of partial discharge with one or several parameters. Many studies around the world have shown that long-term predictions of the development trend of partial discharges are very difficult. But, the partial discharge in a short time is relatively stable. Therefore, we can extract linear characteristic quantities from the characteristic fingerprint of PD, and use those linear quantities to predict the development trend of discharge for a short time. Short-term prediction can obtain the discharge development trend within a few minutes or hours before the failure occurs and realize the

failure warning, which is also very meaningful in engineering.

In this paper, the aging experiment platform of GIS PD defect model is built. Three typical GIS defect models are designed for accelerated aging test and the UHF detection technology is used to collect the PD signal. Finally, the ARMA prediction model is introduced to predict the development trend of partial discharge in a short-term.

## 2 EXPERIMENTAL SETUT

### 2.1 Test Circuit Setup and Test Model

Figure1 shows the 220 kV GIS partial discharge test platform. TC1 and TC2 are two test chambers for setting the discharge defect model. S1 and S3 are internal UHF sensors, and S2 and S4 are external UHF sensors that receives PD signals radiated by a defect discharge inside the cavity through a pouring hole at the disc insulator. The partial discharge signal coupled by the sensor is processed by the signal conditioner, then, one channel is connected to the oscilloscope, and the other is uploaded to the computer via the embedded data processing unit. The oscilloscope is Agilent MSO9404A with a sampling rate of 20 GSa/s and a bandwidth of 4 GHz.

In this experiment, three defect models are designed, which are the suspension defect on the high voltage side, surface discharge defect and suspension defect on the ground side. The model of suspension defect on the high voltage side is formed by placing a shield on the high voltage conductor of GIS and making the shield contact with the conductor incompletely. The model of suspension defect on the ground side is formed by placing the M10 bolt at the interface between the disc insulator and the shell of GIS. The surface discharge model is formed by sticking a 3 cm metal wire on the surface of disc insulator with sticky tape. Three defect models are shown in Figure 2, Figure 3 and Figure 4, respectively. The last step is to place the defect models in the test chamber filled with SF6 gas with a pressure of 0.5 MPa.

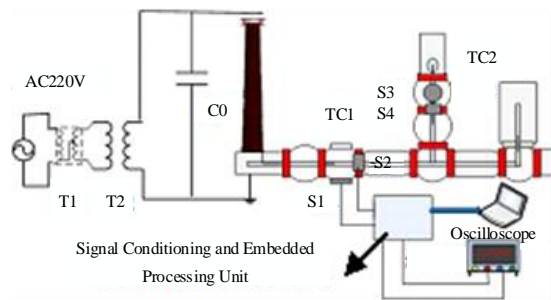


Figure 1. The schematic of test.

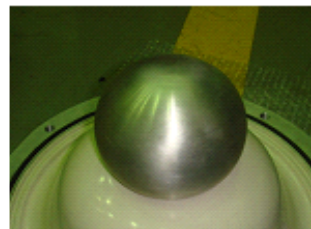


Figure 2 .Suspension defect on the high voltage side in GIS.



Figure 3. Suspension defect on the ground side in GIS.

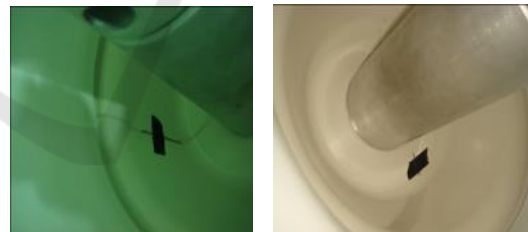


Figure 4. Insulation surface discharge defect in GIS.

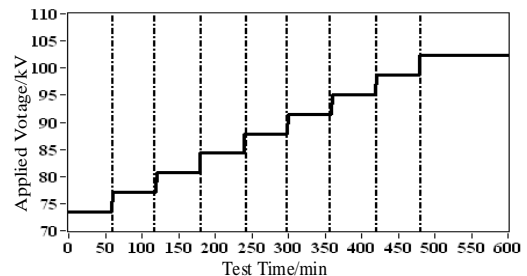


Figure 5.The test voltage curve of suspension defect on the high voltage side

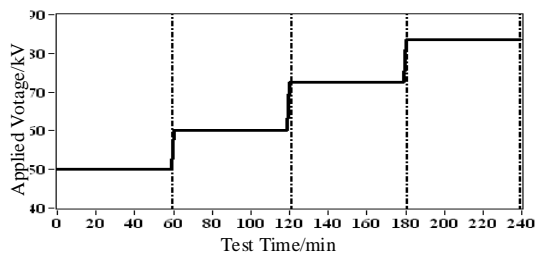


Figure 6. The test voltage curve of suspension defect on the ground side.

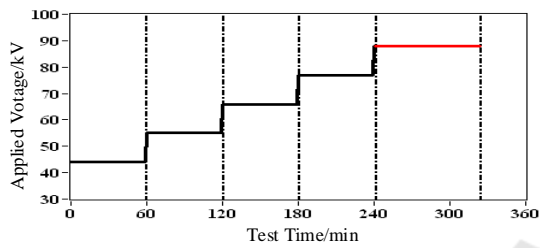


Figure 7. The test voltage curve of surface discharge defect.

## 2.2 Experimental Process

Firstly, the voltage applied to the high voltage side of the GIS is slowly increased until stable PD signals appear, and then the voltage is increased step-by-step to accelerate the degradation of the defect. Taking the test of suspension defect on the high voltage side as an example, when the applied voltage reaches 73.5kV, relatively stable PD signals appeared. Then the voltage was increased step by step and maintained 1 hour at 73.5, 77, 80.5, 84, 87.5, 91, 94.5, 98kV respectively. Then, in order to further accelerate the degradation of the defect, the voltage was raised to 102 kV, and then the test was stopped after keeping the voltage at 95 kV for 2 hours. The curve of applied voltage of floating defect is shown in Figure 5, and the curve of applied voltage of surface discharge defect and insulator-metal discharge defect are shown in Figure 6 and Figure 7 respectively.

It should be specially noted that in the final stage of the test of surface discharge, the voltage was risen to 85 kV, and flashover occurred after 1 hour and 25 minutes.

## 3 THE PREDICTION PRINCIPLE OF ARAM MODEL

### 3.1 ARMA Model

Auto-regressive and moving average (ARMA) Model is a kind of stochastic time series model, which is widely used in various fields (Yang, Chen, Shen, 2018; Kang, Qi, Liu, 2012). It usually uses the random characteristics of time series to describe the evolution of a phenomenon, that is, it uses the past and current values of time series and the weight of the random disturbance factor to model and predict the evolution of time series. ARMA is an important method to study time series.

Auto-regressive (AR) model and moving average (MA) model are important time series model. The AR model predicts future values by a linear combination of past observations and current interference values, and the MA predicts future values by a linear combination of past interference values and current interference values. ARMA model is a combination of AR model and MA model, and its mathematical formula is

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (1)$$

In this formula,  $y_t$  is time series;  $\phi_i$  and  $\theta_i$  ( $i=1, 2, 3, \dots, p$ ) is indefinite coefficient,  $p$  and  $q$  are order of the model;  $\varepsilon_t$  is the deviation due to interference.

Some time series are sets of time-dependent variables. Although there is uncertainty in the single value of the time series, the whole sequence changes regularly which can be described by relevant mathematical models. That is the basic idea of using ARMA model to predict the development trend of partial discharge. Mathematical models help to understand the structure and characteristics of time series fundamentally, and contribute to obtain the optimal prediction in the sense of minimum variance. Therefore, it is very suitable to analyze short-term process of PD by means of math models and predict the development trend.

### 3.2 Procedures of Modeling

Procedures of modeling is shown in Figure 8 and detailed steps are as follows.

(1) Calculate the values of the sample auto correlation function (ACF) and the sample partial auto correlation function (PACF).

The formula of ACF is

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k} (x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^n (x_t - \bar{x})^2} \quad (2)$$

And the formula of PACF is

$$\hat{\phi}_{kk} = \frac{\hat{D}_k}{\hat{D}} \quad (3)$$

There are two matrix in the formula of PACF, those are

$$\hat{D} = \begin{pmatrix} 1 & \hat{\rho}_1 & \cdots & \hat{\rho}_{k-1} \\ \hat{\rho}_1 & 1 & \cdots & \hat{\rho}_{k-2} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\rho}_{k-1} & \hat{\rho}_{k-2} & \cdots & 1 \end{pmatrix} \quad (4)$$

And

$$\hat{D}_k = \begin{pmatrix} 1 & \hat{\rho}_1 & \cdots & \hat{\rho}_1 \\ \hat{\rho}_1 & 1 & \cdots & \hat{\rho}_2 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\rho}_{k-1} & \hat{\rho}_{k-2} & \cdots & \hat{\rho}_k \end{pmatrix} \quad (5)$$

(2) Selected and fitting the ARMA (p, q) model with appropriate order according to the characters of the ACF and PACF.

(3) Estimate the values of indefinite coefficient in the model.

After fitting the model, the next step is to estimate the unknown coefficient in the model.

(4) Verify the validity of the model.

A valid model means that the model contains almost all the information of the data, so that the residual does not contain any relevant information, this is, residual is white noise series. Therefore, white noise test need to be performed for the residual of fitted model. If the results of the test show that the residual is not white noise, the model is considered to be not valid. in this case, other models need to be considered.

If the fitted model passes the white noise test, then steps (2)-(4) continue to be performed to establish multiple fitted models with full consideration of various possibilities. and selecting

the optimal model from all the fitted models that pass the test.

(5) Optimizing the model.

The optimal model is selected from all the fitted models that pass the test. Akaike information criterion (AIC) is a standard used to weigh the goodness of fit, and evaluate the complexity of the model and the ability of the model to fit the data. The more parameters of the model, the wider the range of models that can be selected and the more accurate the model is. However, with the increase of parameters, the parameter estimation is more and more difficult, and the accuracy of estimation is getting lower. Therefore, a good model should reach a certain balance between the accuracy of the model and the accuracy of parameter estimation.

Usually, AIC is defined as  $AIC = -2\log(\text{maximum likelihood value of the model}) + 2(\text{number of unknown parameters of the model})$ . The model with the smallest AIC value is the optimal model.

(6) Use the fitted model to predict the future trend of the series.

## 4 SHORT-TERM PREDICTION OF PARTIAL DISCHARGE

### 4.1 Short-term Prediction for Linear Characteristic Parameters of PD

By processing the test data of the suspension discharge on the high voltage side, the variation curve of the discharge phase width is shown in Figure 9. The discharge phase width varies linearly with the test time, so its data is selected to evaluate the accuracy of the development trend of linear characteristic parameters of PD predicted by the ARMA prediction model. The total test time is 600 minutes and the data of the first 200 minutes is used to model and predict the development trend of partial discharge phase width in different time periods.

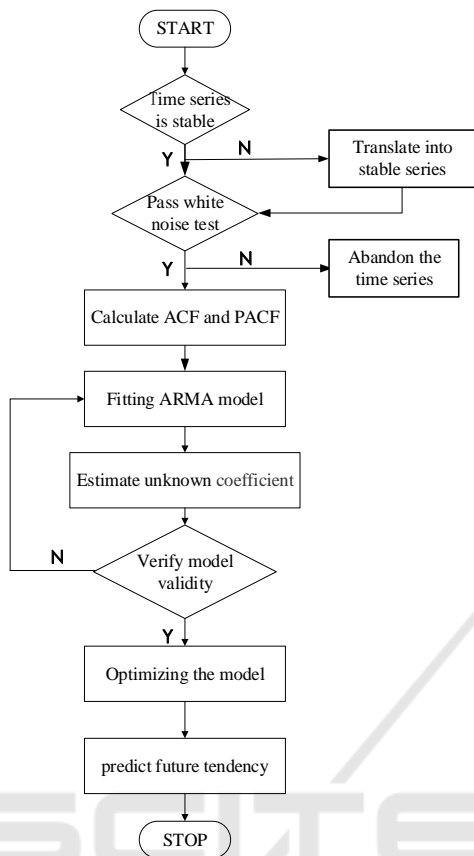


Figure 8. ARMA modeling process.

As can be seen from Figure 10, the predicted values differ little from the true values with different prediction times. It can be seen from the relationship between the prediction time and the prediction error shown in Figure 11. In the range of the prediction time of 0-400, the prediction error is kept within 10%, which indicates that for the linearly varying partial discharge characteristic parameter, it is feasible to predict short-term trend by ARMA model.

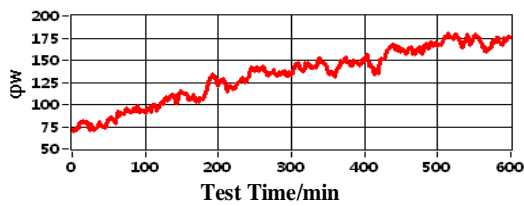
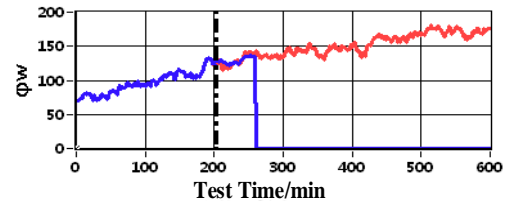
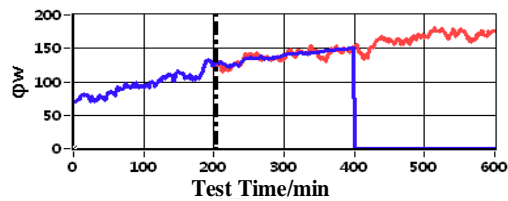


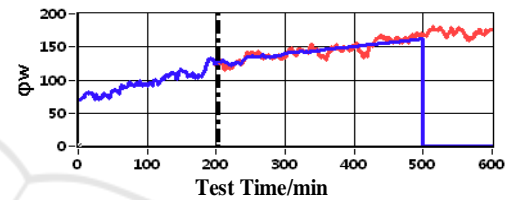
Figure 9. The change trend of phase width of suspension discharge on the high voltage side.



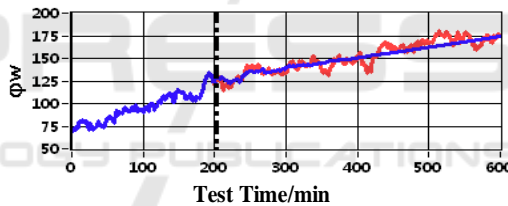
(a) The curve of 50 minutes prediction



(b) The curve of 200 minutes prediction



(c) The curve of 300 minutes prediction



(d) The curve of 400 minutes prediction

Figure 10. Predicted curves in different prediction time.

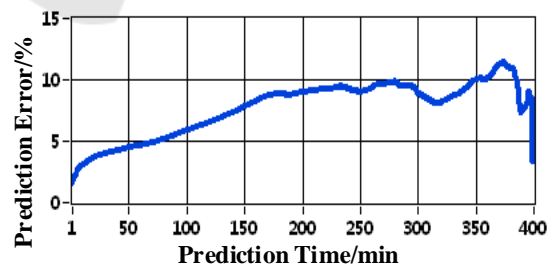


Figure 11. Predicted error with different prediction time.

#### 4.2 Short-term Prediction for Step Characteristic Parameters of PD

By processing the test data of the suspension discharge on the ground side, the variation curve of the discharge interval number is shown in

Figure 12. The discharge interval number of the insulator-metal discharge step increase with the test time, so its data is selected to evaluate the accuracy of the development trend of step characteristic parameters of PD predicted by the ARMA prediction model. The total test time is 240 minutes and the data of the first 150 minutes is used to model and predict the development trend of discharge interval number in different time periods.

It can be seen in the Figure 13 that as the prediction time increases, the difference between the predicted value and the true value gradually widens. As shown in Figure 14, when the prediction time is less than 30 minutes, the prediction error can be kept within 10%, and then the error increases with the extension of the prediction time. The reason of increase of subsequent prediction error is that the third step of the true value changes less than the first two. In general, the ARMA model cannot accurately determine the size of the step, but it can predict the development trend of step characteristic parameters of partial discharge roughly.

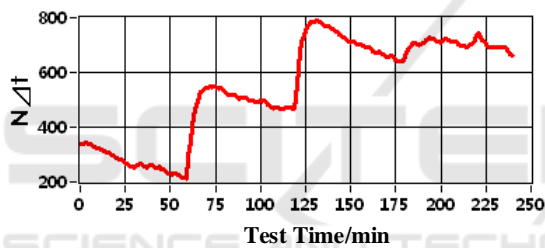
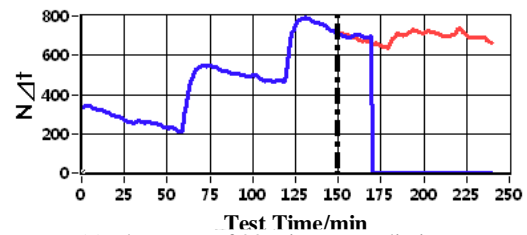


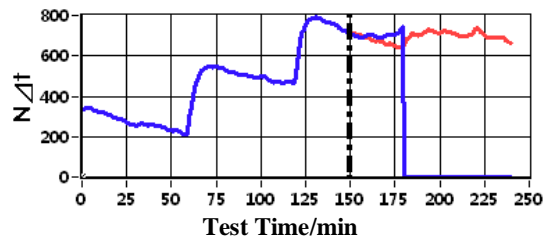
Figure 12. The change trend of discharge interval number of suspension discharge on the ground side.

### 4.3 Short-term Prediction for Irregular Characteristic Parameters of PD

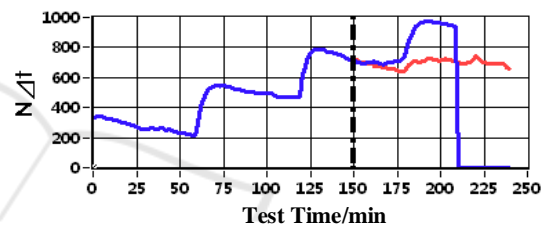
By processing the test data of the insulation surface discharge, the variation curve of the information entropy of discharge amplitude is shown in Figure 15. The information entropy of insulation surface discharge amplitude increase with the test time irregularly, so its data is selected to evaluate the accuracy of the development trend of irregular characteristic parameters of PD predicted by the ARMA model. The total test time of insulation surface discharge is 386 minutes and the data of the first 250 minutes is used to model and predict the development trend of discharge interval number in different time periods.



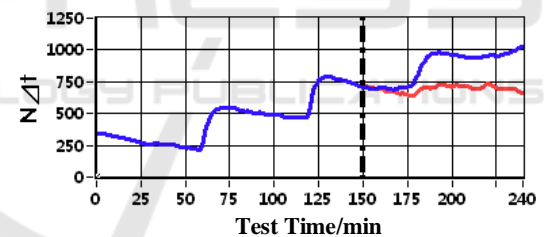
(a) The curve of 20 minutes prediction



(b) The curve of 30 minutes prediction



(c) The curve of 60 minutes prediction



(d) The curve of 90 minutes prediction

Figure 13. Predicted curves in different prediction time.

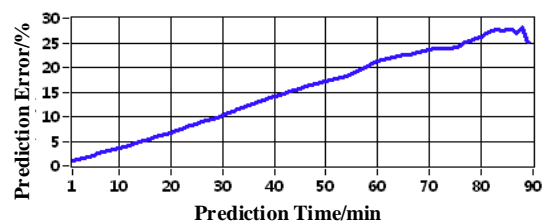


Figure 14. Predicted error in different prediction time.

It can be seen from Figure 16 and Figure 17 that as the prediction time increases, the difference between the predicted value and the true value increases rapidly, and the prediction error is greater than 10%, which indicates that it is difficult for the

ARMA model to accurately predict the trend of irregular characteristic parameters. However, the ARMA model can predict the approximate trend, as shown in Figure 16.

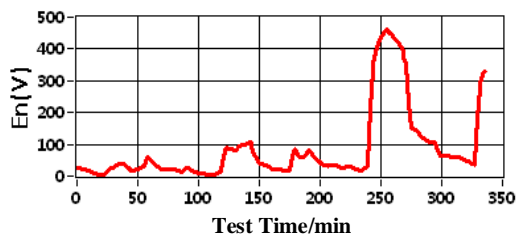


Figure 15. The change trend of entropy of insulator surface discharge amplitude width with test time.

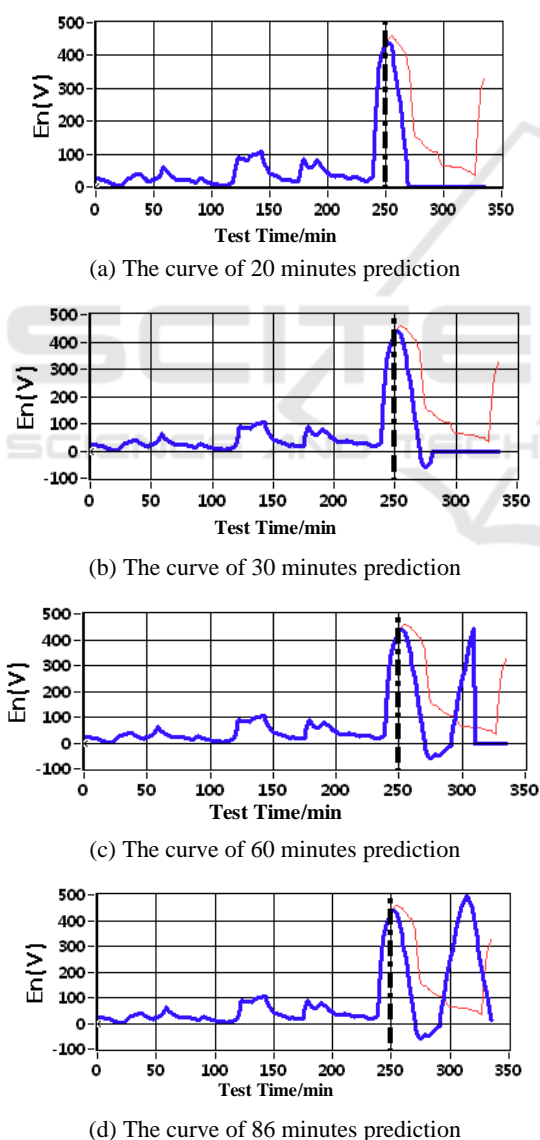


Figure 16. Predicted curves in different prediction time.

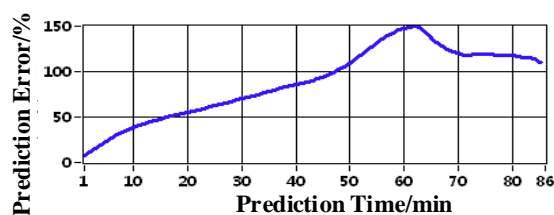


Figure 17. Predicted error in different prediction time.

## 5 CONCLUSION

In order to obtain the partial discharge data of typical defects, a partial discharge test platform containing three kinds of defects and was built in this paper, and experiments were carried out. Aiming at the early warning of fault caused by partial discharge defect, the ARMA model prediction theory and the process of modeling are introduced in detail. Based on the obtained partial discharge data, the ARMA model was used to predict the development trend of partial discharge, and the prediction results were analysed. Finally, the following conclusions were obtained.

(1) The effect of short-term prediction of ARMA model is different for the characteristic parameters with different development trends. For linear characteristic parameters of partial discharge, the ARMA model can accurately predict the short-term trend of the characteristic parameters, and the prediction error is smaller; for the partial discharge characteristic parameters with step change, when the prediction time is less than 30 minutes, the prediction error is less than 10%. But the prediction error will increase with the extension of the prediction time. For the irregular characteristic parameters of partial discharge, the prediction effect of ARMA model is not good. The ARMA model can roughly predict short-term trend of irregular characteristic parameters, but it is difficult to make accurate prediction.

(2) In the substation, the on-line detection system can collect the partial discharge signal in real time and analyse the variation trend of the typical characteristic parameters. Based on these parameters, appropriate prediction model can be selected to predict the development trend of the partial discharge, which is of great significance for fault warning and stable operation of electrical equipment.

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## REFERENCES

- Bolin, P., and Koch, H., 2005. Introduction and applications of gas insulated substation (GIS), *IEEE Power Engineering Society General Meeting*.
- Кучинский, Г. С., 1984. Partial discharge of high voltage electrical equipment, China Water Conservancy and Electric Power Press.
- Kang, H. , Qi, Y. , Liu, G., et al., 2012. Application of the ARMA Model in Non-stationary Vibration Signals. *International Conference on Quality, IEEE.*
- Li. J., Sun, C.X., Du, L., et al., 2002. Study on Fractal Dimension of PD Gray Intensity Image. *Proceedings of the CSEE*, 22, p. 123-127,.
- Liu, Y.P., Lv, F.C., and Li, C.R., 2004. Study on pattern spectrum of partial. *Proceedings of the CSEE*, 24, p.179-183.
- Liu, Y. P., Wang, Z. J., Li, Y. S., 2013. Study on the Insulating Spacers Surface Discharge of GIS. *Applied Mechanics and Materials*, 385-386, p. 1209-1212.
- Martin, Y., Li, Z., Tsutsumi, T., et al., 2012. Detection of SF<sub>6</sub> Decomposition Products Generated by DC Corona Discharge Using a Carbon Nanotube Gas Sensor. *IEEE Transactions on Dielectrics and Electrical Insulation*, 19, p. 671-676.
- Okubo, H., Kato, T., Hayakawa, N., et al., 1998. Temporal Development of Partial Discharge and Its Application to Breakdown Prediction in SF/sub 6/ gas. *IEEE Transactions on Power Delivery*, 13, p. 440-445.
- Pharmatrisanti, A., Meijer, S., and Smit, J. J., 2004. Probability of Partial Discharge Detection in Aged GIS due to Void in Epoxy. *Gaseous Dielectrics X. Springer US*.
- Qiu, Y.C., 1994. GIS device and its insulation technology, China Water Resources and Electric Power Press.
- Qi, B., Li, C.R., Hao, Z., et al., 2011. Evolution phenomena and features of surface partial discharge initiated by immobilized metal particles on GIS insulators, *Proceedings of the CSEE*, 31(1), p. 101-108.
- Qi, B., Li, C.R., Xing, Z.L., et al., 2014. Partial Discharge Initiated by Free Moving Metallic Particles on GIS Insulator Surface: Severity Diagnosis and Assessment. *IEEE Transactions on Dielectrics and Electrical Insulation*, 21, p. 766-774.
- Ren, M., Dong, M., and Qiu A.C., 2014. Partial Discharges in SF<sub>6</sub> Gas Filled Void under Standard Aperiodic and Oscillating Switching Impulses. *IEEE Transactions on Dielectrics and Electrical Insulation*, 21, p. 262-272.
- Strachan, S.M., McArthur, S.D.J., Judd, M.D., et al, 2005. Incremental Knowledge-based Partial Discharge Diagnosis in Oil-filled Power Transformers. *Intelligent Systems Application to Power Systems*, 130, p.181-186.
- Tang, Z.G., Tang, M.Z., Li, J.Z., et al, 2017. Review on Partial Discharge Pattern Recognition of Electrical Equipment. *High Voltage Engineering*, 7, p.173-187.
- Yang, Q., Chen, S.Z., Shen, S.M., et al., 2018. Adaptability of LSTM Network and ARMA Modeling to Random Error Prediction of Inertial Devices. *Electronics Optics & Control*, 25, p. 68-72.
- Zhou, Q., Tang, J., Tang, M., et al, 2006. Mathematical Model of Four Typical Defects for UHF Partial Discharge in GIS. *Proceedings of the CSEE*, 26, p. 99-105.