

# Analysis of Microgap Electrostatic Discharge Parameters With Algorithms of Neural Network and Wavelet Transform

Fangming Ruan<sup>1b</sup>, Senior Member, IEEE, Kai Xu, Yang Meng<sup>2b</sup>, Member, IEEE, Wenli Wang, Sheng Guan, Kui Zhou<sup>3b</sup>, Cheng Yang, and Yanli Chen

**Abstract**—Special relationship exists between environmental conditions and discharge characteristic parameters in microgap electrostatic discharge (ESD) events. Potential relations between input and output of neural network can be explored if taken discharge environmental factors as neural network input. The characteristic parameters of discharge results are affected by environmental conditions, and hence, discharge parameters can be described with an output of neural network. Circumstances factors effect on discharge parameters in microgap ESD result was analyzed with two algorithms of neural network wavelet transform combined with Kalman filter. Nonlinear relationship between circumstances conditions and discharge result effect was a feature in microgap ESD events. Strong positive relationship existed between discharge parameters and circumstances factors of electrode moving speed, gas pressure, and temperature. Characteristic parameters measured in real ESD experiment were compared to predictive parameters of calculation result from neural network algorithm. The analysis of accuracies was given on the prediction of discharge process trend compared to discharge current data measured in experiment. Noise in discharge current waveforms can be suppressed effectively with the method of wavelet transform combined with Kalman filter.

**Index Terms**—Characteristic parameters, electrostatic discharge (ESD), Kalman filter, neural network, wavelet.

## I. INTRODUCTION

**D**ISCHARGE result in real electrostatic discharge (ESD) events may be changed much with different circumstances factors, even if voltage on charged object is identical in multiple test times. Daoud et al. [1] proposed the viewpoint of electrode approach speed affecting on rise slope in discharge

Manuscript received 17 December 2022; revised 18 May 2023; accepted 16 July 2023. Date of publication 30 August 2023; date of current version 12 October 2023. This work was supported in part by the Guizhou Province Project of Science and Technology Innovation and Creation Talents Team of Electrostatic and Electromagnetic Protection under Grant QKHP-TRC [2017]5653, in part by the National Nature Science Foundation of China under Grant 62062025 and Grant 62102112, and in part by the Science and Technology Foundation of Guizhou Province Key Program under Grant [2019]1432. The review of this article was arranged by Senior Editor S. J. Gitomer. (Yang Meng is co-first author.) (Corresponding author: Fangming Ruan.)

Fangming Ruan, Wenli Wang, Cheng Yang, and Yanli Chen are with the School of Big Data and Computer Science, Guizhou Normal University, Guiyang 550025, China (e-mail: 921151601@qq.com; 290250243@qq.com; 86307802@qq.com; yanli\_027@qq.com).

Kai Xu is with the Liupanshui Vocational College, Liupanshui 553100, China (e-mail: 525064980@qq.com).

Yang Meng is with the Mechanics Institute of China Academy of Science, Beijing 100190, China (e-mail: 707382823@qq.com).

Sheng Guan is with Guiyang Network Technology Company Ltd., Guiyang, Guizhou 550025, China (e-mail: 1367191571@qq.com).

Kui Zhou is with Fiberhome StarrySky Company, Nanjing 210000, China (e-mail: 1337217630@qq.com).

Color versions of one or more figures in this article are available at <https://doi.org/10.1109/TPS.2023.3298800>.

Digital Object Identifier 10.1109/TPS.2023.3298800

0093-3813 © 2023 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.

See <https://www.ieee.org/publications/rights/index.html> for more information.

Authorized licensed use limited to: National Science Library CAS. Downloaded on April 12, 2024 at 06:57:24 UTC from IEEE Xplore. Restrictions apply.

current. Other researchers [2], [3], [4], [5], [6] paid more attention for electrode moving speed and circumstances effect on discharge parameters. During applying the international standard [7] IEC61000-4-2 for practice measurement of ESD, test results have usually shown discreteness and low repeatability. Some potential relationship, as a matter of fact, may exist between discharge parameters and circumstances factors of electrode moving speed, gas pressure, and temperature. Neural network [8], as the basic method of deep learning and artificial intelligence (AI), has been applied and extended into various fields of research [9], [10], [11], [12], [13], [14]. In order to search the relationship of discharge parameters changed with circumstances factors, a neural network can be applied for ESD events process analysis. Electrode moving speed, temperature, and gas pressure can be viewed as self-variables and used as input variables of a neural network. In contrast, characteristic parameters in ESD process are viewed as the function of input variables in neural network. So, potential relationships were researched on discharge results parameters varied with circumstances factors through analyzing the relationships between the output and input of a neural network. Based on neural network algorithms and wavelet transform combined with Kalman filter, investigation was performed on potential extrapolation relationship of discharge parameters variation with circumstances factors and on noise suppression in discharge current in the ESD process. The properties of discharge parameters in microgap ESD events, considering the effect of circumstances factors, were described through algorithms related to AI and wavelet transform.

The structure in this paper was arranged as the following: at the first, introduction was given on research background in Section I, then a special new measurement system of ESD was described in Section II for further effect discussion of circumstances conditions on discharge result parameters. In Section III, the effect of circumstance factors on discharge parameters was analyzed based on a neural network algorithm and the real data measured in the experiment with new ESD measurement system. In Section IV, the analysis of noise suppressing in ESD current waveform was given with the algorithm of a wavelet transform and Kalman filter. At the last, in Section V, a conclusion was provided.

## II. SPECIAL MEASUREMENT SETUP

ESD result may be affected by various circumstances factors. Our team has researched and created a special experiment system [15] used to investigate the effect of electrode moving speed on discharge result parameters in ESD event.

The new ESD measurement system structure (seen in Fig. 1) consists of the following sections.

- 1) Sealed chamber.
- 2) Crankshaft connecting rod.

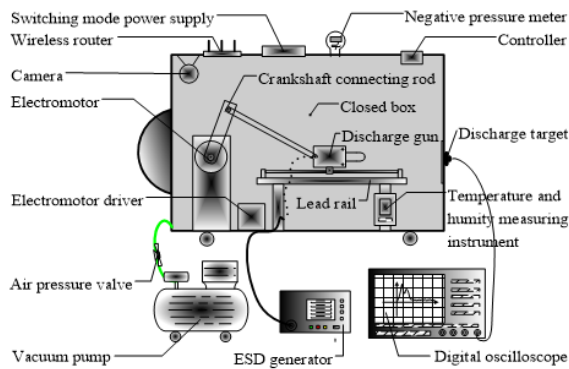


Fig. 1. New experimental system of electrode moving speed effect in ESD.

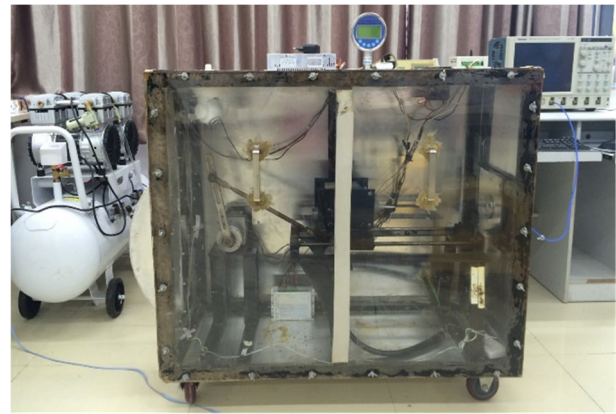


Fig. 2. Picture of the new ESD experiment setup for speed effect investigation.

- 3) Driving motor with controlling module.
- 4) ESD generator (ESD gun).
- 5) Discharge target.
- 6) Gas pressure meter and controller.
- 7) Temperature and humidity meter.
- 8) High-voltage supply.
- 9) Digital oscilloscope.
- 10) Vacuum pump, camera, and wireless router.

Discharge target is mounted on a sidewall of the sealed chamber. Driving motor is fixed on the holder at the bottom of the chamber. ESD gun can be moved forward and backward along the guide rails between the motor and the discharge target. Gas pressure in the closed chamber can be adjusted through controlling a vacuum pump connected to the sealed chamber with a pipeline. Gas pressure meter is fixed on the top surface of the box, which displays real-time negative pressure value in the chamber.

A Tektronix digital oscilloscope (BW2.5 GHz, sampling rate 40 GHz) is connected to the discharge target for measurement data acquisition. Discharge current waveforms are stored and displayed by the oscilloscope. The new ESD experiment prototype setup is shown in Fig. 2.

ESD experiment was performed under initial conditions of starting temperature  $T = 20\text{ }^\circ\text{C}$  and relative humidity of  $\text{RH} = 56$ , respectively. ESD result may be varied much for different speeds of electrode moving to the target, even the charge voltage applied to ESD gun is identical in different test times. With moving electrode (fixed on the front terminal of ESD gun) at different speeds to the target, the discharge parameters of current peaks, rise time, peak of current derivative, and gap length can be measured and calculated in the experiment of ESD with the new experimental setup.

Changing frequency in control module of step motor, one can adjust the speed of electrode moving to the target. The speed range of moving electrode to the target is in 1–100 cm/s. Discharge parameters' difference may be drastically remarkable due to slow speed and large speed of moving electrode. The larger the speed of electrode moving speed to the target, the higher the peak value of discharge current, the steeper of rise slope in discharge current, and the shorter of arc length.

### III. EFFECT ANALYSIS OF CIRCUMSTANCES ON DISCHARGE PARAMETERS WITH NEURAL NETWORK

In real ESD events, discharge result can be affected by various factors in circumstances. The investigation of relationship between circumstances factors and discharge parameters will be benefit to the protection of electronic equipment and

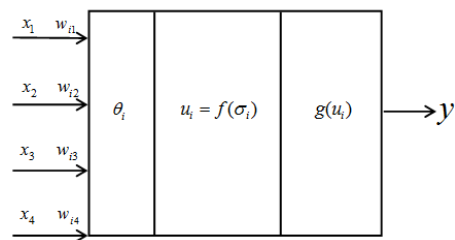


Fig. 3. MP model of neural network.

device from the harm of ESD. The simulation of experiment, in the following section, with a linear neural network was used to discuss the effect on discharge parameters of different circumstances factors. A neural network model (as shown in Fig. 3) proposed by W. S. McCulloch and W. Pits (the so-called MP model) can be a useful tool to analyze discharge result parameters in ESD events.

Based on neural network model shown in Fig. 3, three main steps were considered as follows.

- 1) Supplying input data and obtaining output data.
- 2) Substituting the data and conducting circling training.
- 3) Determining prioritized value and the threshold value.

Assuming  $N$  neurons are interconnected, the activation state of any one neuron  $x_i$  ( $i = 1, 2, 3, \dots, N$ ) is 1 or 0, representing excitement or inhibition, respectively. Training process is much important in the whole linear simulating process.

The error of neural network in the training process is a multidimension paraboloid. Training process is based on the principle of the least square root of gradient fall. The best solution is the basement for a linear neural network, as the learning rate is low enough.

A model can be established based on the previous analysis related to discharge parameters variation; input variable and output variables can also be determined with the establishment of the model. Initial data come from measurement result with the experimental system of ESD. Main circumstances factors during the process of ESD taking place include electrode moving speed to the target, gas pressure, temperature, and relative humidity. Electrode moving speed effect on discharge current parameters and influence on discharge current rise time of gas pressure will be discussed in the following.

TABLE I  
LINEAR MODEL INPUT AND OUTPUT DATA OF ESD  
AFFECTED BY ELECTRODE MOVING SPEED

<b>Input</b>	moving speed speed(m/s)	0.05 0.09 0.13 0.18 0.22 0.27 0.31
<b>output1</b>	peak current(A)	1.56 1.70 1.99 2.14 2.23 2.26 2.56
<b>output2</b>	rise slope(A/ns)	0.96 1.24 1.64 1.88 1.92 2.01 2.13
<b>output3</b>	fall slope(A/ns)	1.84 2.23 2.48 2.61 2.84 2.85 2.81
<b>Input</b>	moving speed speed(m/s)	0.35 0.39 0.42 0.45
<b>output1</b>	peak current(A)	2.47 2.58 2.61 2.63
<b>output2</b>	rise slope(A/ns)	2.32 2.48 2.60 2.71
<b>output3</b>	fall slope(A/ns)	2.89 2.96 3.10 3.22

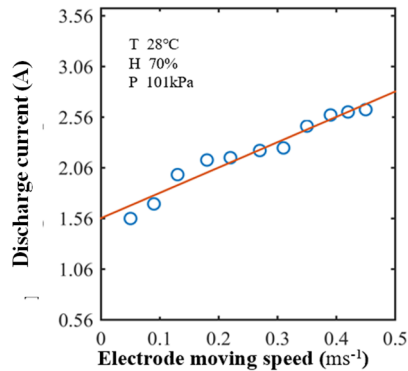


Fig. 4. Relationship of peak discharge current with electrode moving speed.

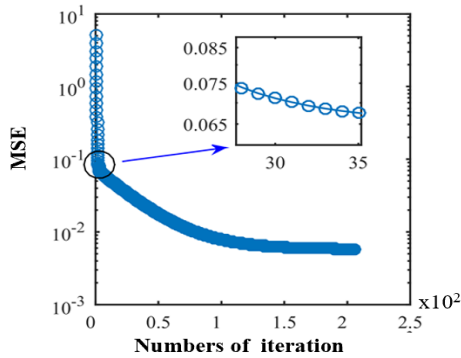


Fig. 5. Relationship between iteration number and mean square error.

#### A. Effect on Discharge Current Parameters of Electrode Moving Speed

The speed moving electrode to the target has strong influence on discharge parameters (seen in Table I).

It can also be seen in Table I that three output variables correspond to one input variable, which denotes that the process of three linear fitting calculations will be performed separately. Based on the data in Table I, the fitting result was given in Fig. 4.

The analysis of relationship between discharge parameters and electrode speed moving to the target can be exerted. According to the data measured in ESD experiment, peak current values increase with an electrode speed moving to the target. The relationship between peak current of ESD and electrode moving speed can be seen distinctly through the linear fitting to the data measured.

With the increase of iteration number, mean square error, seen in Fig. 5, falls rapidly at first and then approaches gradually flat, which means the best-fitting straight line. Good agreement has been obtained by the comparison of results between theoretical analysis and neural network analysis. The consequence has verified distinctly that strong positive

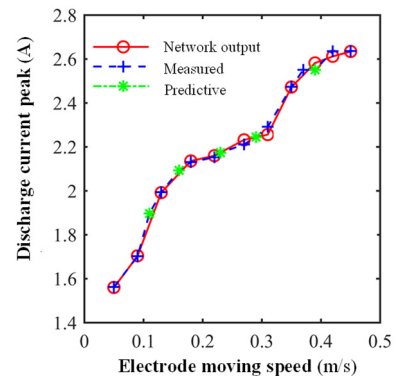


Fig. 6. Electrode moving speed on discharge current peak values obtained, respectively, by practical measurement, network output, and BP neural network prediction.

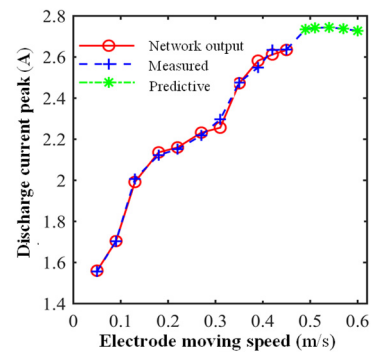


Fig. 7. Potential of electrode moving speed on discharge current peak values obtained, respectively, by practical measurement, network output, and BP neural network prediction.

co-relationship exists between electrode moving speed to the target and discharge current peak values.

Discharge current peak values variation with circumstances factors can be predicted with back propagation neural network (BP neural network) method plus genetic algorithm. Shown in Figs. 6 and 7 are discharge current peak values obtained by real experiment measurement, network output, and BP neural network plus genetic algorithm, respectively, in which discharge current peak potential change was predicted in Fig. 7. Difference of discharge current peak values between measured and predictive ones with BP neural network is given in Fig. 8, in which maximum (0.078), minimum (0.009), and average (0.0479) values of the difference are also provided. The accuracy of predictive discharge current peak values with BP neural network algorithm was shown in Table II. As shown in Table II, the predictive accuracy of all data exceeds 90%.

#### B. Effect Analysis of Gas Pressure on Rise Slope Time With Neural Network

After optimization with genetic neural network, the simulation of relationship between gas pressure and rise time in discharge current is shown in Fig. 9. Fitting degree of training compared to real data, seen from Fig. 9, is much high because of applying genetic neural network, reached much good effect than the traditional network. Potential variation of rise time in discharge current can be seen in Fig. 10. On the other hand, Table III provided comparison between measured data and predictive data. The accuracy degree of all predictive data, seen in Table III, is over 90%.

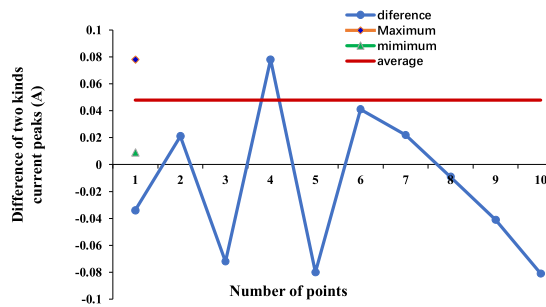


Fig. 8. Difference of discharge current peak values between measured and predicted with BP neural network and maximum, minimum, and average values.

TABLE II

ACCURACY OF PREDICTION BY COMPARISON BETWEEN MEASURED PEAK VALUES OF DISCHARGE CURRENT AND PREDICTIVE ONES

Electrode moving speed (m/s)	0.11	0.16	0.23	0.29	0.39
Peak values measured (A)	1.884	2.088	2.182	2.232	2.56
Predictive values (A)	1.85	2.109	2.11	2.31	2.48
Accuracy (%)	98.2	99.0	96.7	96.5	96.9
Electrode moving speed (m/s)	0.49	0.51	0.54	0.57	0.6
Peak values measured (A)	2.692	2.72	2.754	2.782	2.816
Predictive values (A)	2.733	2.742	2.745	2.741	2.735
Accuracy (%)	98.4	99.2	99.7	98.5	97.2

TABLE III

DATA COMPARISON BETWEEN REAL MEASURED RISE TIME AND PREDICTIVE RISE TIME WITH GENETIC BP NETWORK

Gas pressure (MPa)	0.067	0.079	0.087	0.091	0.099
Measured rise time (ns)	0.73	0.75	0.76	0.76	0.78
Predictive rise time (ns)	0.73	0.72	0.71	0.71	0.74
Accuracy (%)	100.0	96.0	93.4	93.4	94.9

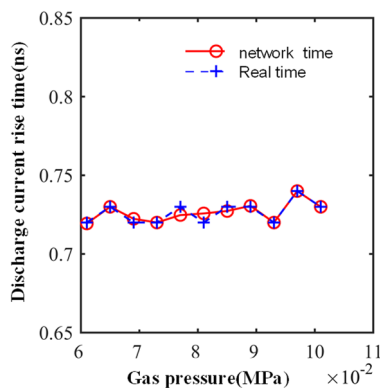


Fig. 9. Measured and BP network predictive relationships between gas pressure rise time and gas pressure.

#### IV. NOISE SUPPRESSING IN ESD CURRENT WITH WAVELET TRANSFORM AND KALMAN FILTER

Noise suppressing is a special concerned task in ESD current analysis. In signals analysis and processing wavelet transform is a much useful tool. A function, based on wavelet transform and its associate inversion formula, can be

decompose into weighted sum of its various frequency components. The main idea suppressing noise with wavelet transform is that selecting proper wavelet function and layers of decomposition, which are used to process discharge current signal. Outline information in ESD current waveform, in wavelet scaling coefficients, mainly locates in low-frequency area, but noise in ESD current waveform mainly locates in high-frequency area. Wavelet transform scaling coefficients corresponding useful outline information in discharge current have the features of comparative large amplitude and less coefficient number.

On the other hand, wavelet scaling coefficients corresponding noise have the feature of small amplitude values and multiple coefficient number.

Noise suppressing with the threshold value of wavelet transform has the following steps.

- 1) Wavelet transform in one dimension—selecting proper wavelet and decomposing layers( $N$ ), calculating scaling coefficient at layer  $N$  (low-frequency region), and calculating coefficients on layers  $1 \sim N$  (high frequency).
- 2) Quantification of wavelet coefficient threshold values—noise of ESD current distribute mainly in wavelet coefficients; setting proper values for wavelet coefficients at various layers; and making quantification of threshold values.
- 3) Wavelet reconstruction of one dimension signal—reconstructing suppressed noise ESD current signal based on wavelet coefficients after processing with wavelet transform coefficients and threshold method.

How to select threshold values and their quantification are key steps in processing the signals, which has direct impact on effect suppressing noise. Method selecting threshold values in wavelet transform, therefore, can be used to process various layers of wavelet transform coefficients and then reconstruct current signal and realize objective to suppress noise.

Kalman filter is a recursive algorithm of linear minimum variance estimation, which is used to process random signal and has no deviation. Kalman filter is used to estimate signal-based system equations and observed equations, which use observed noise and system noise data as an input, while use predictive estimation values (state and parameters in system) as an output [16].

ESD current signals can be decomposed with the selection of proper wavelet function and decompositive multiple layers [17]. The information of outline on ESD current, when considering frequency spectrum of ESD current waveform, mainly distributed in the low-frequency range. The noise in discharge current waveform, however, is located in the range of high frequency. Noise in ESD current waveform, therefore, can be suppressed by removing high components in wavelet decomposition coefficients. The block diagram was given in Fig. 11, suppressing noise in ESD current waveform. ESD current waveform shown in Fig. 12 is the measured result in the experiment of ESD with a special setup of ESD [15]. The waveforms shown in Fig. 13 include two discharge current waveforms, the red line represented that processed discharge current waveform in Fig. 12 with wavelet transform, while the blue line shown result processed that in Fig. 12 by wavelet plus Kalman filter. As shown in Fig. 13, a comparative good effect of noise suppression has been obtained through wavelet transform threshold values separation method and wavelet transform plus Kalman filter.

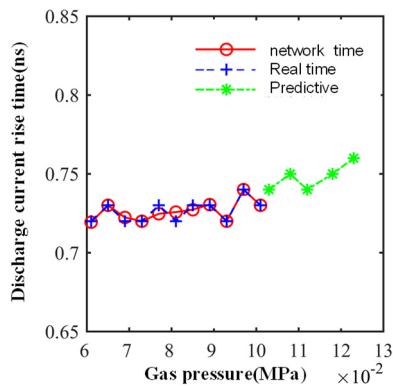


Fig. 10. Measured and succeeding values predicted with genetic BP network on relationships between gas pressure and rise time.

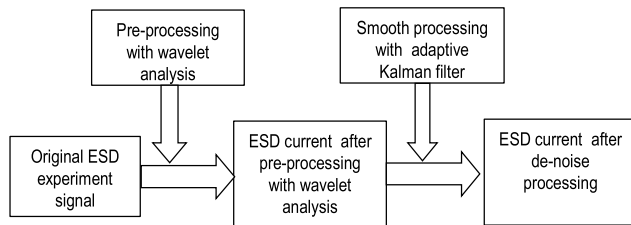


Fig. 11. Block diagram of ESD analysis with wavelet transform and Kalman filter method.

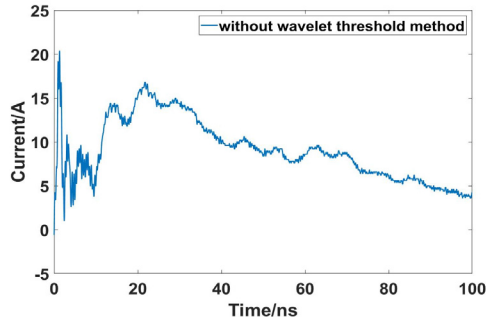


Fig. 12. Discharge current before being processed with wavelet threshold method.

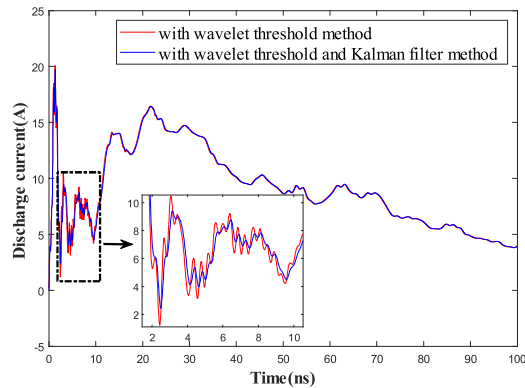


Fig. 13. Comparison of noise suppression in discharge current with two methods.

Comparing difference of discharge current waveforms between red line in Fig. 13 and discharge current waveform in Fig. 12, the spikes (thorns) of red line in Fig. 13 are much less than that in Fig. 12. The effect suppressing noise has been distinctively with wavelet threshold method. If combined wavelet transform with Kalman filter, the effect suppressing noise can be improved more clearly. After being presuppressing with wavelet transform, adaptive Kalman filter algorithm was used to process the ESD current waveform. The blue line

in Fig. 13 is the result processed discharge current in Fig. 12 with waveform transform plus Kalman filter.

As shown in Fig. 13, discharge current waveform shown by blue line has been purified more fluent and smoother than that shown by red line. The spike number in discharge current waveform (blue line), compared to the discharge current waveform (red line), was much less than that in the latter (shown by red line), and hence, the discharge current curve after processing with wavelet transform plus Kalman filter shown smooth remarkably than that without processing, in particular in the range of high frequency.

## V. CONCLUSION

Two algorithms related to AI and wavelet transform were employed to analyze the effect of circumstances factors on ESD result parameters and to suppress noise in discharge current. Circumstances conditions variation by changing electrode moving speed to the target and changing gas pressure can strongly impact on discharge result parameters. Based on the large number of experimental data measured under changing electrode moving speed and gas pressure, neural network algorithms have been applied to analyze and predict variation of rise time and peak value of discharge current. The prediction results agreed well with that measured in ESD experiment. Noise in the discharge current waveform of ESD can be suppressed effectively with the method of wavelet transform combined with Kalman filter. The consequence in this work may provide some reference for proposing a new test standard on noncontact ESD test in coming time.

## REFERENCES

- [1] B. Daoud, H. Ryser, A. Germond, and P. Zwiackner, "The correlation of rising slope and speed of approach in ESD," in *Proc. 7th Int. Symp. Electromagn. Compat.*, Zurich, Switzerland, 1987, pp. 467–474.
- [2] D. Pommerenke, "On influence of speed of approach, humidity and arc length on ESD breakdown," in *Proc. 3rd ESD Forum*, Grainau, Germany, 1993, pp. 103–111.
- [3] W. D. Greason, "Methodology to simulate speed of approach in electrostatic discharge," *J. Electrostatics*, vol. 44, nos. 3–4, pp. 205–219, Sep. 1998.
- [4] T. Ishida, Y. Tozawa, and O. Fujiwara, "Effect of approach speed on spark length determining air discharge current from ESD generator in environment with different temperature and humidity," in *Proc. IEEE Int. Joint EMC/SI/PI EMC Eur. Symp.*, Jul. 2021, pp. 1153–1158.
- [5] Q. Yuan, X. Zhang, and S. Liu, "Analysis on the relative factors affecting the characteristics of air electrostatic discharge," *High Voltage Eng.*, vol. 36, no. 10, pp. 2500–2506, Oct. 2010.
- [6] F. Ruan and T. Dlugosz, "Analysis of partial vacuum formation and effect on discharge parameter in short gap ESD," *Electr. Rev.*, vol. 87, no. 2, pp. 292–293, Feb. 2011.
- [7] *Electromagnetic Compatibility (EMC)—Part 4-2: Testing and Measurement Techniques—Electrostatic Discharge Immunity Test*, 2nd ed., IEC Standard 61000-4-2, 2008.
- [8] Z. He, *MATLAB R2015b Neural Network Technology*. Beijing, China: Tsinghua Univ. Press, 2016.
- [9] G. Yang, C. Zheng, and X. Sun, "An experimental study on partial discharge pattern recognition method based on wavelet neural network," *J. Harbin Univ. Sci. Technol.*, vol. 10, no. 5, pp. 98–101, Oct. 2005.
- [10] L. Song, T. Zhan, and Z. Ai, "Simulation of electrical signal output with linear neural network," *Exp. Tech. Manag.*, vol. 27, no. 7, pp. 87–88, 2010.
- [11] H. Wen and G. Zhao, "Lineare neural network realization based on neural network toolbox in MATLAB," *Electron. Tech.*, vol. 2005, no. 1, pp. 27–30, 2005.
- [12] C. Luo, "BP network realization based on neural network toolbox in MATLAB," *Comput. Simul.*, vol. 21, no. 5, pp. 109–111, 2004.

- [13] D. Wang, L. Wang, and G. Zhang, "Predictive model of short time wind speed based on BP neural network," *J. Zhejiang Univ., Eng. Ed.*, vol. 2012, no. 5, pp. 837–841, 2012.
- [14] X. Lin, Q. Jiang, and T. Xiong, "A prediction model based on BP neural network," *Res. Develop. Comput.*, vol. 43, no. z3, pp. 338–343, 2006.
- [15] F. M. Ruan, X. D. Yang, Z. L. Li, F. Zhou, Y. Meng, and X. Wang, "Test instrument of electrode moving speed effect and its manufacturing method," China Patent, 2013 10 017 269.6, Dec. 3, 2014.
- [16] Y. Qin, H. Zhang, and S. Wang, *Kalman Filter and Principles of Group Navigation*. Xi'an, China: Press of Northwest China Univ. Industry, 1998, pp. 33–41.
- [17] K. Zhou, F. Ruan, and J. Zang, "Air dynamics analysis on electrode moving speed effect," *Chin. J. Radio Sci.*, vol. 31, no. 6, pp. 1060–1066, Dec. 2016.



**Fangming Ruan** (Senior Member, IEEE) was born in Guizhou, China, in March 1958. He received the B.S. degree in electronic engineering from Guizhou University, Guiyang, China, in July 1982, the M.A. degree in education from Guizhou Normal University, Guiyang, in July 2006, and the Ph.D. degree in electronic engineering in electromagnetic fields and electromagnetic waves from the Beijing University of Post and Telecommunication, Beijing, China, in July 2009.

He was affiliate with the Liupanshui Normal College, Liupanshui, China, as a Teacher, in August 1982. In February 2000, he transferred to Guizhou Normal University, Guiyang, as an Associate Professor. Since December 2006, he has been a Full Professor with Guizhou Normal University. He has published more than 100 papers in academic journals and academic conferences. He is the owner of four patents. His research interests include electrostatic discharge and electromagnetic compatibility, effect of electromagnetic circumstances, big data and private protection, and protection of internet from attack.

Dr. Ruan is a Senior Member of the China Institute of Electronics (CIE) and the China Institute of Communication (CIC), a member of Director Commission of the China Institute of Cyberspace Security, and an Expert in Academician Liu Shanghe Research Station of the 5th Academy of China Aerospace Group Companies.



**Kai Xu** was born in Guizhou, China, in January 1987. He received the B.S. degree in environmental engineering and the M.S. degree in environmental engineering from Zhejiang University, Hangzhou, China, in July 2012 and December 2017, respectively.

He was affiliate with the Liupanshui Vocational Technical College, Liupanshui, China, as a Teacher, in April 2018. He has published more than ten papers in academic journals, owning three patents. For the past few years, his research field was environmental protection, including the hazards and prevention of electrostatic discharge.



**Yang Meng** (Member, IEEE) was born in Shandong, China, in April 1989. He received the Ph.D. degree in optical engineering from the Institute of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications, Beijing, China, in 2019.

He is currently a Research Associate with the Mechanics Institute of China Academy of Science, Beijing, and a Research Fellow with Nanyang Technological University, Singapore. He used to be a Post-Doctoral Fellow at the Department of Biomedical Engineering, School of Medicine, Tsinghua University, Beijing. His major is in optical engineering and mainly studies the 3-D display and photoelectric information processing. His research interests include 3-D display, photoelectric information processing, electromagnetic compatibility, and electrostatic discharge.



**Wenli Wang** was born in Guizhou, China, in June 1984. He received the B.S. degree in automation and the M.E. degree in control engineering from the Wuhan University of Science and Technology, Wuhan, China, in July 2008 and June 2016, respectively.

He was affiliate with Guizhou Normal University, Guiyang, China, as a Teacher, in 2017. He holds six patents, two of which are invention patents and four utility model patents. In the past few years, his research field was electrical control and electromagnetism.



**Sheng Guan** was born in Hubei, China, December 1992. He received the B.S. degree in electronic information science and technology from the Hubei Institute of Science and Technology, Xianning, China, in July 2016, and the M.E. degree in electronic science and technology from Guizhou University, Guiyang, China, in July 2019.

He was with Guiyang Network Technology Company Ltd., Guiyang, as an Engineer. His research interests include EM software application in engineering design.



**Kui Zhou** was born in Henan, China, in October 1991. He received the B.S. degree in electronic information engineering from the Qingdao University of Technology, Qingdao, China, in June, 2015, and the M.S. degree in electronic science and technology from Guizhou University, Guiyang, China, in June 2018.

He was affiliate with Fiberhome StarrySky Company Ltd., as an Engineer, in July 2018. For the past few years, he has published four papers in academic journals. His research interests include data analysis and data mining and the hazards and theory of electrostatic discharge.



**Cheng Yang** was born in Guizhou, China, in February 1979. He received the B.S. degree in physics from Guizhou Normal University, Guiyang, China, in June 2002, the M.S. degree in computer application technology from Guizhou University, Guiyang, in June 2010, and the Ph.D. degree in communication and information systems from Wuhan University, Wuhan, China, in December 2017.

He was affiliate with Guizhou Normal University, as a Teacher, in July 2002. He has published more than 20 papers in academic journals, owning six patents. For the past few years, his research fields were 3-D audio simulation, 3-D electromagnetic field simulation, and voiceprint recognition.

Dr. Yang is an Executive Member of CCF and TCVRV.



**Yanli Chen** received the B.S. and Ph.D. degrees from Southwest Jiaotong University, Chengdu, China, in 2008 and 2019, respectively.

She is currently an Associate Professor with the School of Big Data and Computer Science, Guizhou Normal University, Guiyang, China. Her research interests include covert communication, information hiding, and digital forensics.