3D Modeling Technology Based On Computer Aided Environment Design

Feng Li1,*, Wenbing Xi1, Xin Dai1
1Jiangsu Electric Power Company Huai’an Power Supply Company, China, 223002

*Corresponding author e-mail: lifeng@jspec.com.cn

Abstract. Voltage violation of the distribution network greatly affects the power supply quality and the user’s power consumption experience. To better improve the voltage quality of the power grid, real-time analysis of voltage violation can help power grid personnel to handle voltage violation instantly and efficiently through analyzing the attribute indicators on distribution network lines. However, many studies are concerned only with the single voltage violation cause, and ignore the more complicated phenomenon of voltage violations. In this paper, we proposed a joint attributes based neural network multi-classification (JANN) model that takes mutual influence between attributes from different nodes in the distribution network into account when voltage violations are detected. Concretely, we construct the set of joint attributes from each node in the distribution network though real-time monitoring of the power grid. Then the joint attribute based neural network model is constructed to analyze the voltage violation phenomenon, and determine the cause multi-classification of voltage violations. Experimental results show that the proposed (JANN) method can reach 95.79% F1-score rate on multi-classification of voltage violation causes.

Keywords: Analysis of the Causes of Voltage Violations, Joint Attributes, Neural Network Multi-classification Model

1. Introduction
With the increase demand of people's electricity usage, which also leads to the unprecedented increase in the grid size of the power grid. In some regions, voltage violations occur frequently because power distribution equipment cannot completely support the rapid increase in total power load. Therefore, a large number of researchers focus on analyzing the causes of voltage violation [1-2]. Voltage violations refer to the fact that the voltage at the end of the distribution network exceeds the scope of the national standard [3]. Moreover, in order to maintain the power system efficiently, the causes of voltage violations should be analyzed immediately when voltage violation occurs at the end of the distribution network. And there are many reasons for voltage violations, including low bus voltage, line overloads, Medium voltage circuit or equipment failure and etc [4-5]. In order to reduce human involvement in the analysis of voltage violations, the construction of complex optimization equations, and conduct a more comprehensive analysis of voltage violations. In this paper, we proposed a joint
at-tributes based neural network multi-classification (JANN) model to classify the multi-class of voltage violation causes. First, based on the attributes of each node in the distribution network actually monitored by the power grid, we build a set of joint attributes by encoding the value of these attributes. Then we construct a fully connected neural network model to classify the causes of voltage violations by training the joint attribute set.

Consequently, the main contributions of this paper can by summarized as follows:

Propose a joint attributes based method for analyzing voltage violations. The interactions between different nodes in the distribution network are fully taken into account in the set of joint attributes.

Present a fully connected neural network multi-classification model to analyze the causes of voltage violation by training the joint attribute set. This model provides a more comprehensive analysis of voltage violation causes and the multi-classification of voltage violation causes is more realistic.

The remainder of this paper is organized as follows. Section 2 presents research relating to analysis of the causes of voltage violations. Section 3 give a complete description of JANN model for analyzing the causes of voltage violations. We discuss the experimental results in Section 4. Finally, Section 5 conclude this paper and proposes the future direction.

2. Related works

Among the numerous causes of voltage violations, there are several common causes that most studies focus on, such as bus voltage problem, loading problem, Underload problem and etc [6-7]. They divide the whole distribution network into a series of segments, and monitor the relative difference of input and output current of a segment to detect fault in the distribution network. Sivokobylenko et al. focus on Neutral ground fault in medium-voltage (3-35kV) electrical networks [8]. They model the medium-voltage network to learn the behavior of the medium-voltage network. In fact, in addition to these causes of voltage violations mentioned above, there are a number of other possible cause categories including medium voltage line or equipment failure, unreasonable distribution network transformer gear and etc. In many literatures on the causes of voltage violations, optimization-based method are widely used to detect faults in distribution networks, the optimization is solved by using quadratic programming. In [9], it proposed a probabilistic load-flow-based approach to monitor voltage quality in distribution networks. However, the complexity of mathematical modeling increases with the complex structure of the distribution network. And the optimal solution of the model is also a difficult problem to solve.

Besides, with the rapid development of knowledge in the field of deep learning, neural network-based methods have been applied to various fields, such as computer vision, Speech Recognition, medical and etc. And neural network-based methods achieved excellent result in these fields. In [10], a bat-neural network multi-agent system (BNMNAS) is used to predict stock price, and it use quarterly data of the DAX price from 1972-04 to 2012-07 to train and test BNNMAS. The experimental results show that the results predicted by the BNNMAS can greatly fit the real prices. In [11], it construct a deep convolutional neural network to extract features from short texts for multi-modal sentiment analysis. In [12], a Deep Structured Semantic Models is proposed to learn the similarity between users and items through mapping users and items into a shared latent semantic space. Their experimental results show that the method they proposed helps improve the recommendation quality.

3. Algorithm

In JANN model, we focus on proposing a multi-class voltage violation analysis model that take mutual influence between attributes from different nodes in the distribution network into account. We also adopt a fully connected neural network to analyze the voltage violation phenomenon and determine the cause multi-classification of voltage violation. First, we collect and encode the joint attributes from different nodes in the distribution network. Then based on these collected attributes, we propose a fully connected neural network model to analyze the voltage violations. Finally, multi-cause classification
of voltage violations are predicted through a softmax dense.

3.1. Construction of Joint Attributes
It is known that the line structure of the distribution network is generally complicated and there are many nodes on the line. And the mutual influence between attributes of each node in the distribution network play a significant role in the classification of voltage violations. For examples, the power supply radius and bus voltage are useful to classify whether the reason of voltage violations belongs to the unreasonable setting of transformer gear in distribution network. Therefore, we construct the set of joint attributes from each node in the distribution network though real-time monitoring of the power grid, which includes attribute values of 137 dimensions.

3.2. B. Neural Network Multi-classification Model
After collecting and encoding the joint attribute set from distribution network, a fully connected neural network multi-classification model is presented to improve the accuracy of the voltage violation causes classification by learning mutual influence between joint attributes. Specifically, Since the dimension scale of the joint attribute set is small, there is no problem of parameter explosion of the model. And contribution of all features to the objective function is consistent in the fully connected neural network, we adopt the fully connected neural network to learn the intrinsic relationship in all of attributes by extracting the more potential features of the joint attribute set. Furthermore, a classifier is constructed by adopting the results of the fully connected neural network. Finally we utilize the classifier to achieve cause multi-classification of voltage violation.

(1) Fully Connected Neural Network: Given the network structure of the fully connected neural network an input sequence x0, x1, ..., xn, which in this paper is a set of joint attributes, including dimensional attribute values. The output h = h’, h”, ..., h’s of the hidden layer is defined via the following function.

\[ W = [W0, W1, ...Ws]^T \]  
\[ h’ = W * [x0, x1, ...xn]^T \]  

Where We Rs\times n is the weight matrix of the hidden layer and h’ e Rs\times0.

Besides, choosing the suitable activation function is also an indispensable step in the process of constructing a neural network model. Common activation functions include the sigmoid function and the tanh function, but both of these activation functions have problems with gradients disappearing when training neural network models. Moreover, the former is limited in speed when updating the weight gradient of the neural network. Therefore, in order to improve the convergence speed of the neural network and avoid the disappearance of the gradient, we adopt the ReLu function as the activation function. The definition of ReLu function is max (0, x).

Finally, after nonlinear processing of the output of the hidden layer node by the activation function, we obtain the ultimate output heRs\times0 of the fully connected neural network.

(2) Multi-classification Model: Given a discrete set of cause classes C for voltage violations, we expect to build a multi-classifier that predicts the cause label y’ from this cause classes C by exploiting the output of fully connected neural network. Therefore, we use a softmax classifier to predict the cause label y’, and the classifier takes the output h calculated of the fully connected neural network as input.

\[ y’ = \text{softmax} (W h + b) \]  

3.3. C. Extraction of measurement ontology
This article considers that the use of previous methods may lead to the emergence of many irrelevant entities, so this article adopts the method of manually formulating rules for matching to extract entities. First, the expert specifies the entity rules in the power document, and then this article matches the various entities of the metering document according to the string matching method, a total of 7 types
In addition, we expect to maximize the probability of the correct prediction, or minimize the cross-entropy error between the predicted distribution $y^*$ motivated by this expectations, given model parameters $\theta$ ($W, W_t, b_t$), we adopt negative log-likelihood of the true cause label $y_k \in \mathcal{C}$ and $L2$ regularization as the cost function.

$$J(\theta) = -\frac{1}{t} \sum_{k=1}^{t} y^k \log \hat{y}^k + \frac{\lambda}{2} \| \theta \|^2_2$$ (4)

Where $t$ is the number of cause labels in the cause classes $\mathcal{C}$. $\lambda$ is an $L2$ regularization hyperparameter.

### 3.4. Training for JANN Model

In the training process of JANN model, the parameters $\theta$ ($W, W_t, b_t$) of JANN model are updated by using the back propagation algorithm. For the softmax layer, let’s $\delta_t \in \mathbb{R}^{s \times 0}$ be the softmax error:

$$\delta_t = (W_t (y^* - y)) \odot f'(h)$$ (5)

Where is the Hadamard product between the two vectors and $f'(h)$ is the element-wise derivative of $f(h) = \tanh(h)$. Besides, the softmax layer backpropagates its error to the fully connected neural network layer. Therefore, the error $\delta_h \in \mathbb{R}^{n \times 0}$ of the fully connected neural network layer is related to $\delta_t$ and the input $x \in \mathbb{R}^{n \times 0}$ of the layer.

$$\delta_h = (W \delta_t) \odot f'(x)$$ (6)

Where $f'(x)$ is the element-wise derivative of $f(x) = \text{ReLu}(x)$. Finally, we choose the adaptive learning rate based optimizer adam to improve the convergence speed of JANN model when updating the weight matrix with the weight gradient.

### 4. Experiments

To evaluate JANN model, we collect 3000 data on the voltage violations from July to October 2019. 2000 of them are used as training sets, and the remaining 1000 are used as test sets.

#### 4.1. Evaluation Metrics

In our experiments, we apply several metrics to evaluate the performance of JANN model. For cause multi-classification of voltage violations, the classification labels for each sample in the dataset and robustness of JANN model from multiple aspects, including similarity measures, precision rate, recall rate and F1-score.

1. **Jaccard Index**: Jaccard index is the best evaluation indicator that reflects the similarity between JANN model prediction results and the real classification labels. It is defined as the ratio of the number of correctly predicted to the number of all classification labels for a sample.

$$\text{Jaccard index} = \frac{1}{D} \sum_{i=0}^{D} \frac{|T_i \cap P_i|}{|T_i \cup P_i|}$$ (7)

Where $T_i$ and $P_i$ present the true label and JANN model prediction result of the $i$th sample, respectively $D$ is the number of sample in the test set.

2. **Precision Rate**: In order to more intuitively evaluate the performance of JANN model, we also use precision rate to illustrate the accuracy of JANN model classification. Given a sample to be predicted, the define of precision rate is the ratio of the number of correctly predicted to the number of labels corrected predicted by JANN model to the total number of labels predicted by the JANN model.

$$P = \frac{1}{D} \sum_{i=0}^{D} \frac{|T_i \cap P_i|}{|T_i \cup P_i|}$$ (8)

Recall rate: Precision rate can only reflect the capability of JANN model to correctly predict the classification label, but it cannot report the generalization ability of JANN model. Therefore, we also
adopt the recall rate to evaluate the robustness of JANN model. Given a sample to be predicted, it is defined as the ratio of number of correctly predicted to the number of real classification labels of the samples (table 1).

\[ F_1 = \frac{2 \times P \times R}{P + R}. \]

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|}
\hline
Method & Jaccard Index & Precision Rate & Recall Rate & F1-score Rate \\
\hline
Expert experience based classification method & 89.93 & 90.27 & 89.41 & 88.64 \\
SVM & 93.23 & 93.52 & 93.30 & 92.74 \\
DT & 92.04 & 92.57 & 91.64 & 91.26 \\
JANN model & 96.01 & 96.12 & 96.13 & 95.74 \\
\hline
\end{tabular}
\caption{Multi-classification results of different classification methods (In %)}
\end{table}

4.2. Experiment Results

In order to verify the performance of JANN model for the analysis of voltage violations. We first conduct an experiment to evaluate multi-classification performances of proposed JANN model for voltage violations by using the evaluation matrix presented in the previous section. Further-more, we also compare multi-classification performances of voltage violation causes under different classification methods, including decision trees (DT) model, expert experience based classification method and JANN model.

In our experiment, we firstly used 1500 pieces of data as the training set, and the remaining 500 pieces are used as the evaluation set. Finally, we choose the optimal model parameters for subsequent classification experiments. The parameter comparison experiment results of JANN model is demonstrated in Figure 1. The performance of JANN model reaches the peak point when the number of hidden layer nodes is 150, and the multi-classification results of JANN model achieves 96.03% Jaccard index, 96.18% precision rate and 96.17% recall rate, as well as 95.79% F1-score rate. All of the above results show that JANN model can learn the behavior of the distribution network by extracting the more potential interrelationships between the attributes of the distribution network nodes. Therefore, JANN model can more accurately analyze the causes of voltage violation when voltage violation occurs in distribution network.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Multi-classification results of JANN model}
\end{figure}

5. Conclusion and future work

In this paper, we present a joint attributes based method for cause analysis of voltage violations by
constructing the joint attribute set from each node in the distribution network though real-time monitoring of the power grid. Besides, we also propose a neural network multi-classification model to improve the performance of multi-cause classification of voltage violations by extracting the mutual influence between different attributes in the joint attribute set. Experimental result shows that proposed JANN model outperforms the traditional machine learning and expert experience based classification method for the cause analysis of voltage violations.

In the future, we expect to be more aware of the behavior of the distribution network systems by extracting deeper potential influences between the attributes of distribution network nodes. In this way, we can respond in time and analyze the causes when a voltage violation occurs.

**Acknowledgments**

This work was supported by State Grid Science and Technology Projects, J20190108.

**References**

[1] W. Qin, P. Wang, X. Han, and X. Du. Reactive power aspects in reliability assessment of power systems [J]. IEEE Transactions on Power Systems, 2011, 26 (1): 85-92.
[2] K. D. Mcbee, M. G. Simoes. Utilizing a smart grid monitoring system to improve voltage quality of customers [J]. IEEE Transactions on Smart Grid, 2012, 3 (2): 738-743.
[3] M. Kopicka, M. Ptacek, P. Toman. Analysis of the power quality and the impact of photovoltaic power plant operation on low-voltage distribution network [J]. Electric Power Quality Supply Reliability Conference, 2014.
[4] B. A. Robbins, C. N. Hadjicostis, A. D. Dominguez-Garcia. A two-stage distributed architecture for voltage control in power distribution systems [J]. IEEE Transactions on Power Systems, 2013, 28 (2): 1470-1482.
[5] H. I. Shaheen, G. I. Rashed, S. J. Cheng. Optimal location and parameter setting of upfc for enhancing power system security based on differential evolution algorithm [J]. International Journal of Electrical Power Energy Systems, 2011, 33 (1): 94-105.
[6] W. Shao, V. Vittal. Bip-based opf for line and bus-bar switching to relieve overloads and voltage violations [J]. Power Systems Conference and Exposition, 2006.
[7] Z. Boshi, H. U. Zechun, Z. Qian, Z. Hongcai, S. Yonghua. Optimal transmission switching to eliminate voltage violations during light-load periods using decomposition approach [J]. Journal of Modern Power Systems Clean Energy, 2018.
[8] V. Sivokobylenko, V. Lysenko. Numerical simulation of transient ground faults in medium voltage networks [J]. 2017 International Conference on Modern Electrical and Energy Systems (MEES), 2017.
[9] J. M. Sexauer, S. Mohagheghi. Voltage quality assessment in a distribution system with distributed generation---a probabilistic load flow approach [J]. IEEE Transactions on Power Delivery, 2013, 28 (3): 1652-1662.
[10] R. Hafezi, J. Shahrabi, E. Hadavandi. A bat-neural network multi-agent system (bnmmas) for stock price prediction: Case study of dax stock price [J]. Applied Soft Computing, 2015, (29): 196-210.
[11] S. Poria, E. Cambria, and A. Gelbukh. Deep convolutional neural network textual features and multiple kernel learning for utterance-level multimodal sentiment analysis [J]. Conference on Empirical Methods in Natural Language Processing, 2015.
[12] A. M. Elkahky, Y. Song, and X. A multi-view deep learning approach for cross domain user modeling in recommendation systems [J]. The 24th International Conference, 2015.