A Situation Awareness and Early Warning Method for Voltage Instability Risk

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***Abstract*—Voltage stability of distribution network is of great significance for safe and reliable operation of distribution system. Aiming at the unexpected and concealment characteristics of the uncertainty of wind power, component fault and load fluctuation in the complex active distribution network, and the concealment of the voltage instability, a method of rapid perception and early warning for the risk situation of voltage instability in distribution network based on data mining and deep learning was proposed in this paper. Taking into account the uncertain factors of source network load and other factors, through feature extraction and derivative methods, the environment factors, power flow state and equipment state which may cause voltage instability are analyzed, and multi-dimensional feature sets are established. Based on the voltage entropy and the weighted voltage entropy, a method to divide the risk grade of voltage instability is proposed. The voltage instability probability and the severity of the distribution network are considered, and the voltage instability is divided into three grades. The deep learning algorithm is introduced to establish the situation awareness model of voltage instability risk, and the accuracy rate of voltage instability risk prediction is compared. By improving the IEEE37 standard example, the effectiveness of the proposed method is verified, and it can provide effective support for the specific operation and maintenance of distribution network.**

***Index Terms*—Active power distribution network; uncertainty; data mining; deep learning; voltage instability; risk warning**

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I. Introduction

THE large number of access to distributed generation is an inevitable trend for the future development of power grid. The inherent characteristics of the uncertainty of the distributed power supply, the failure of the device components and the load fluctuation, the uncertainty of the charge and discharge of the electric vehicle make the power grid different from the new risk of the traditional power grid[1][2]. In recent years, with the large number of distributed power sources connected to the distribution network, its impact on the stability of the power grid cannot be underestimated. Scholars at home and abroad have gradually transferred from the backbone transmission network to the distribution network [3] [4].

The static voltage stability analysis method is based on the system power flow equation, and the critical point of voltage stability is the point that the system can reach the maximum transmission power in physics, a problem of whether there is a feasible solution to the system power in mathematics [5].There are mainly two methods for calculating the critical point of voltage stability: one is the nonlinear programming method [6] and the other is the continuation power flow method [7].The research content of static voltage stability analysis includes the calculation of voltage stability index under current running state, the weak link of the system, and the control strategy of improving the system voltage stability margin. Among them, the analysis methods include sensitivity analysis, continuation power flow, Eigen structure analysis, modal analysis and singular value analysis, etc. [8]. The static voltage stability of large photovoltaic power station is analyzed by using the characteristic structure method, and the static voltage stability criterion and stability margin of large photovoltaic power station are obtained in [4]. According to the random output characteristics of [9], a static voltage stability assessment method of distribution network based on point estimation and Cornish-Fisher series is proposed in DGs.

In the traditional distribution network, the probability and statistics method is mostly used to judge the voltage instability. Under the new background of DG, the voltage stability of the whole network load node cannot be monitored carefully and intuitively. The introduction of machine learning method makes it unnecessary to consider the network structure, parameters and no additional model of distributed power supply and load. It can get the result of reactive optimal configuration point quickly from the statistical information of historical data, and the calculation speed is fast [10]. Examples of machine learning applications in power grids include: predicting wind farm power output; analyzing the faulted transformers; obtaining customer load profiles; performing dynamic security assessment; enhancing the data debugging in power grid operations; and estimating the stability margins from synchro phasor measurements[11]. A wide range of machine learning applications for power grids may be found in [12].

In view of the above problems, a fast perception and early warning method for voltage instability risk situation in distribution network is proposed in this paper. By analyzing the data characteristics of DG access, the multi-dimensional feature set of environmental factors, power flow state and equipment state that may cause voltage instability is established. The mapping analysis of voltage entropy and weighted voltage entropy and voltage instability index is introduced, and the rating index of instability risk considering the voltage instability probability and severity of distribution network is put forward, and the voltage instability is divided into three risk grades. Through the deep learning algorithm, the situation awareness model of voltage instability risk is established, and the prediction accuracy rate is compared. Finally, an example is given to illustrate the effectiveness of the proposed method.

II. DATA PREPROCESSING

A. Feature Extraction

In this paper, wind and solar power are mainly considered. The uncertainty of wind power generation mainly comes from the uncertainty of wind speed, and the solar energy is mainly dependent on the illumination conditions. Through the investigation of the distribution network information management system [13], the data of temperature, humidity, wind speed and other data in the meteorological information system, the location data of the equipment in the geographic information system, the variable capacity of the production management system, the real-time load data, the monthly maximum load data, and the power outage time and the power outage times in the power information collection system is extracted for classification and prediction of the risk of distribution network instability. The voltage instability feature extraction process is shown in Figure 1.

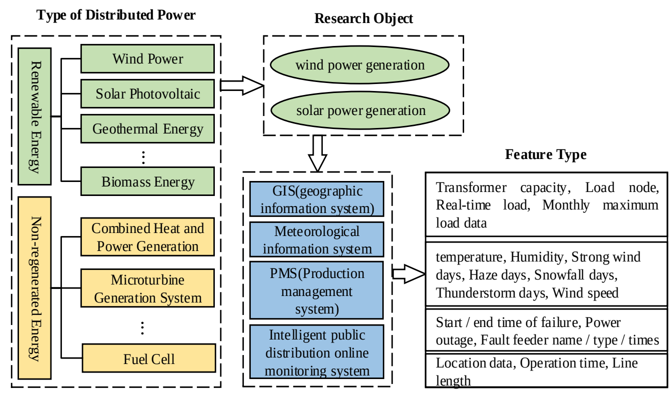

Figure. 1. Flow chart of voltage instability feature extraction

B. Grade division of Instability Risk

In order to quantitatively assess the risk of voltage instability in power systems, information on voltage instability probability and instability consequences is needed. In this paper, voltage entropy and weighted voltage entropy are chosen, and the entropy value decreases with the increase of load margin [14]-[16].

(1) Voltage Entropy

The system has N nodes, where the voltage of node I is V_i, given a constant sequence $U= [U_1, U_2... U_n]$, where $U_1 < \min(V_i)$, $U_n > \min(V_i)$; and n_k represents the number of nodes for $V_i \in (U_k, U_{k+1}]$, $\sum_{k=1}^{n-1} n_k = N$, and the number of nodes in different voltage intervals is probed.

$$P(k) = \frac{n_k}{N} \tag{1}$$

Where: $P(k)$ represents the ratio of the number of nodes $V_i \in (U_k, U_{k+1}]$ the total number of nodes. The voltage entropy of the system is calculated as follows:

$$H = -C\sum_{k=1}^{n-1} P(k)\ln(P(k)) \tag{2}$$

When $P(k)=0$, $P(k)\ln(P(k))=0$; C is a constant, generally satisfying: $0 \leqslant H \leqslant 1$.

It can be seen from the above formula that when the voltage of all nodes is in the same interval, the voltage entropy is 0, which is the most orderly state of the system voltage distribution. When 2 nodes' voltage is not in the same interval, the system voltage entropy reaches the maximum.

$$H_{\max} = -C\ln\frac{1}{n} \tag{3}$$

At this time, the system voltage distribution is the most unbalanced. Once the system is disturbed, the voltage of these nodes is likely to exceed the upper limit or the lower limit, and the loss of the system is also more.

(2) Weighted Voltage Entropy

The node voltage entropy only considers probability distribution of the voltage in each interval, but ignores that the properties in each interval is different, that is to say, the node voltage level is different. For solving this problem, the voltage entropy function is weighted by the inverse of the node voltage mean of each interval. The weighted voltage entropy is defined as follows.

$$H_w = -C\sum_{k=1}^{n-1}\frac{1}{W(k)}P(k)\ln(P(k)) \tag{4}$$

Where: W（k）is the average value of the node voltage V_i ∈（U_k, U_{k+1}]. Since entropy is the index of system voltage order, the more balanced and orderly the distribution of system voltage, the lower the voltage entropy. In order to make the low voltage level correspond to a higher entropy value, the reciprocal of the node voltage mean of each interval is used to weight the voltage entropy function.

Suppose there are t nodes in the interval (U_k, U_{k+1}), the weight is calculated as follows.

$$W(k) = \frac{1}{t}\sum_{i=1}^{t}V_{k,i} \tag{5}$$

Where $V_{k,i}$ denotes the voltage of i-th node in interval（U_k, U_{k+1}].

(3)Severity Index of Instability

The data and state of each feeder partition per month are taken as the statistical analysis object, and the rating index Fi of the power outage fault is obtained.

$$F_i = \frac{2\bullet\sum_{j=1}^{n}\frac{S_{ij}}{S_{iN}}\bullet\sum_{j=1}^{n}\frac{E_{ij}}{E_{iN}}}{\sum_{j=1}^{n}\left(\frac{S_{ij}}{S_{iN}}+\frac{E_{ij}}{E_{iN}}\right)} \tag{6}$$

Where S_{iN} is the capacity of the feeder area i, S_{ij} is the total loss of load in the j power outage accident in this area, E_{ij} is the lack of electricity supply for the j power outage in this area, and N is the total number of power outages in the month.

A three-class problem has been considered, where Level1 represents Operating Points with stability margins that are larger than the mean stability margin value, Level2 for Operating Points with a stability margin in the second quartile, and Level3 if the stability margin is in the smallest quartile.

III. DEEP LEARNING

A. Support Vector Machines

SVM is a machine learning method based on the theory of VC dimension and the minimum principle of structural risk in statistical theory. The main idea is to identify a classification hyper plane, separate the different class sample set and have the largest classification interval. In order to solve the problem of linear inseparable classification, the input space of the sample is converted to the high dimensional space by nonlinear transformation, and the optimal hyper plane is solved in the high dimensional space [17].

B. Artificial Neural Networks

Artificial neural networks, originally developed to mimic basic biological neural systems– the human brain particularly, are composed of a number of interconnected simple processing elements called neurons or nodes. Each node receives an input signal which is the total “information” from other nodes or external stimuli, processes it locally through an activation or transfer function and produces a transformed output signal to other nodes or external outputs [18].

C. Random Forests

Random forests are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. The generalization error for forests converges to a limit as the number of trees in the forest becomes large. The error of a forest of tree classifiers depends on the strength of the individual trees in the forest and the correlation between them [19].

The process of quick perception and early warning of voltage instability risk in distribution network is shown in the figure2.

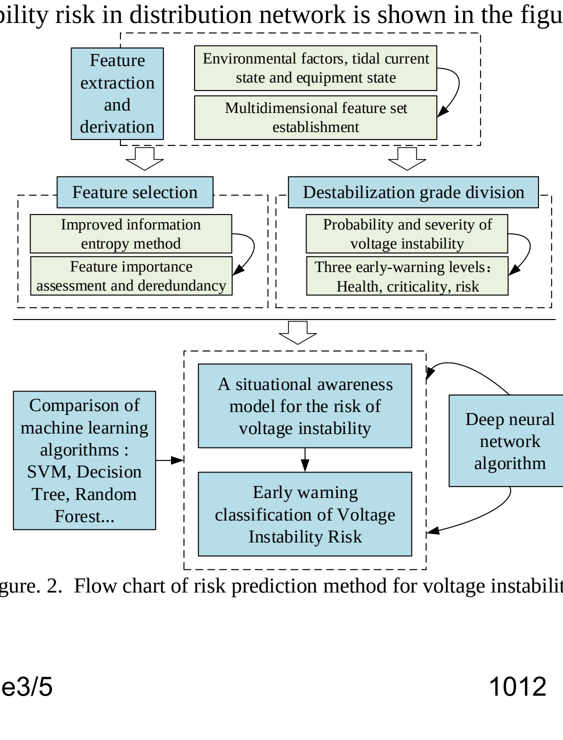

Figure. 2. Flow chart of risk prediction method for voltage instability

IV. CASE STUDY

This example improves the power distribution system of IEEE37 node for example simulation, and obtains all kinds of data through power flow calculation. The system has 37 nodes and 35 branches, of which the rated voltage of the generator is 230kV, the voltage of the 799 node of the bus transformer is 4.8kV, the voltage of the entry system is 4.8kV, and the transformer between the 709 node and the 775 node is 0.48kV. Except for 775 nodes, the rated voltage of the remaining nodes on load is 4.8kV, at 741 nodes, 740 nodes and 735 nodes.

Taking the photovoltaic power supply as an example, 736 nodes are connected to four photovoltaic power sources with capacity of 75kVA, 100kVA, 100kVA and 75kVA respectively. The power flow is calculated by the daily flow mode.

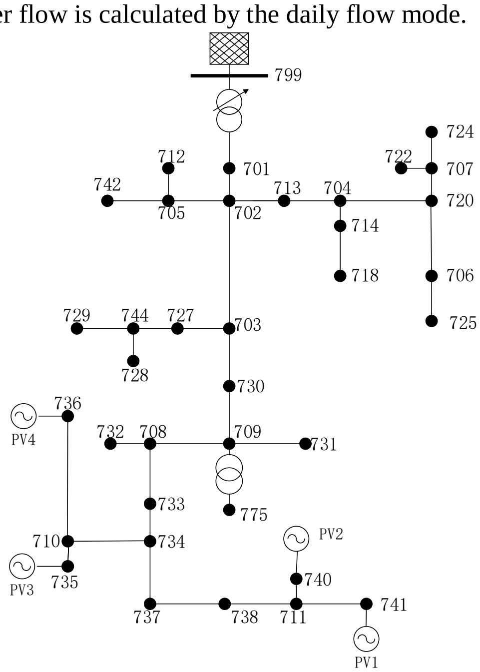

Figure. 3. Improved IEEE37 node system topology

The 740 node single phase node voltage analysis is selected.70% of the historical trend data, equipment status data and PV output data are used as training sets, and 30% of data are used to verify the accuracy of various classification algorithms. In the case of three classes, the following F_1 metric was used.

$$F_1 = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision} \tag{7}$$

Where $Precision = TP / TP + FP$, $Recall = TP / TP + FN$. TP is a positive sample is predicted right, TN is a negative sample is predicted right, FP is a negative sample is predicted wrong, FN is a positive sample is predicted wrong.

The prediction results of different algorithms are shown in Table 1.

TABLE I
THE PREDICTION RESULTS OF DIFFERENT ALGORITHMS

	Support Vector Machines	*Artificial Neural Networks*	*Random Forests*
Level 1	0.8637	0.8767	**0.9290**
Level 2	0.8078	0.8221	**0.8820**
Level 3	0.8290	0.8570	**0.8570**

Table 5 show that the F_1 of the Random Forests algorithm in this paper are 0.9290, 0.8820 and 0.8570 respectively, the comprehensive classification performance is obviously superior to Support Vector Machines and Artificial Neural Networks.

V. CONCLUSION

A reactive power optimization method based on load distribution matching and entropy weight method is proposed in this paper. Through theoretical analysis and numerical simulation, the following conclusions can be drawn:

(1) By analyzing the data characteristics of the distributed power supply, the environmental factors, the state of the power flow and the characteristic set of the equipment may be set up, and the factors of the multi dimension voltage instability are considered.

(2) A classification method of voltage instability risk grade is proposed. The probability and severity of voltage instability in distribution network are considered, and the voltage instability of distribution network is divided into three grades.

(3) Through the deep learning algorithm, the situation awareness model of voltage instability risk is established. The prediction comparison proves the effectiveness of the proposed method.

Because this method needs a lot of historical data to carry out static voltage stability analysis, it is suitable for the distribution network with more perfect historical database and more stable load. For distribution network with fast load growth or imperfect historical database, this method still needs to be matched with the conventional method, and the depth learning method is no more. The application of work optimization needs to be improved and perfected.

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