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A Novel Feature Selection Method for Power System Transient Stability Assessment Based on Interaction Gain

JIANG Zhenyu[1], HU Wei[1*], WANG Kefei[2], YIN Guanhao[3], YUE Han[2*]

1. Power Systems State Key Lab, Dept of Electrical Engineering, Tsinghua University, Beijing 100084, China
2. North East China Grid Company, No. 1, Yingpan North Street, Hunnan New District, Shenyang 110180, China
3. Huadian Fuxin Energy Co., Ltd. Mengdong Branch, Neimenggu 028000, China

ABSTRACT

In modern power system, traditional transient stability assessment(TSA) methods undergo great challenges as the time domain and space structure complexity continue to increase. Taking into account the massive features generated by the power system, in order to avoid the dimensionality disaster problem in artificial intelligence methods and machine learning models, this paper proposes a novel feature selection method. Based on interaction gain, this method measures both the effectiveness and combination effects of certain feature subset, thereby simplifying the original input without information loss. Case study on IEEE 39-bus system TSA verifies the validation in accuracy, false alarms, calculation efficiency and feature size.

Keywords: transient stability assessment, machine learning, information gain, feature subset, AI

NONMENCLATURE

Abbreviations	
AI	Artificial Intelligence
ANN	Artificial Neural Network
BDA	Backward Dropping Algorithm
DT	Decision Tree
EEAC	Extended Equal Area Criteria
IG	Information Gain
ML	Machine Learning
TSA	Transient Stability Assessment

1. INTRODUCTION

Power system has developed rapidly in recent years featured with expansion in the overall system scale and complexity in the grid structure. Also, the growingly high proportion renewable energy and realization of demand response lead to the connection of large numbers of power electronic devices. The diversification and complexity of the temporal and spatial operation characteristics of the power grid poses new challenges to the dispatching operation monitoring and the safe and stable operation [1].

Power system transient stability assessment (TSA) deals with the dynamic behaviour of power system. The judgement of stability within limited time plays an important role in avoiding catastrophic accidents. Traditional analysis methods include simulation in time domain, energy-based direct methods and EEAC [2]. However, these methods are not able to cope with the requirements of modern power system in efficiency, accuracy and capacity [3].

Artificial Intelligence (AI) method, especially data-mining and machine learning technology, is introduced as a promising way to improve online TSA in many aspects. Gabrijel proposes a ANN-based data-mining method to realize the classification of TSA examples [4]. Xue constructs a classification and regression model with a decision tree structure (DT), and points out its advantages in interpretability in the reasonable boundaries of features [5].

Wang and Sawyhney compares the performance of SVM and CVM algorithm in the same features sets observed from power system [6-7]. Wang further builds a deep Q-learning model to realize both online TSA and intelligent flow adjustment at the same time [8].

Unfortunately, most of the existing studies focus on evaluating different AI methods for TSA, but few has given attention to the selection and filtration of fundamental power system feature sets. It makes the generalization performance of these models less effective. In order to avoid curse of dimensionality in ML and to improve the calculation efficiency to meet the demand of actual operation by power system, original input features should be improved in quality by careful and precise feature selection. The target feature set is expected to be both rich enough to best represent the key performance of the original TSA situation, and thin enough to get accurate real-time online TSA result. This paper designs a novel feature selection method for TSA that relies on interaction gain (IG). IG determines the effectiveness and combination effects of certain feature subset. By simplifying the original input without information loss, calculation efficiency and accuracy are guaranteed.

2. PAPER STRUCTURE

The main content of this paper includes following parts:

1) Feature selection method based on interaction gain. This section illustrates the basic information for feature selection and information entropy. The details of interaction gain are then introduced and the overall procedures of feature selection method based on IG is given.

2) Case study and visualization. This section describes physical structure and data generation process of the cases in the first two parts. The last part includes visualized comparison and algorithm validation.

3) Conclusion.

3. FEATURE SELECTION METHOD BASED ON INTERACTION GAIN

3.1 Two-stage feature selection method

It is generally accepted in the field of data-driven AI models that the performance of machine learning has an unsurpassed upper limit. This upper limit is determined by all the data and features involved in the training, and different algorithms and models are only trying hard to find different ways to approach the limit as close as possible. Features are the valuable parts in original data that help to predict the results. Feature engineering in the ML includes the entire process of feature cleaning, selection and reprocessing, and there are two different directions: feature selection and feature extraction.

Feature Selection is like the physical process of screening effective features. The original feature set is acquired through a subset of specific indicators without changing the original meaning of individual features. But feature extraction is more like a chemical process because the original features are reshaped to a low-dimensional space through specific mapping and projection.

The real power system contains a large number of operating components, causing the corresponding features to be extremely large in quantities. Directly applying all the features to subsequent machine learning methods will inevitably reduce the theoretical upper limit of the overall model because of the redundant and irrelevant features. Considering the features of power system operation and analysis, the feature selection method is obviously more advantageous. Firstly, this method has low computational complexity for data samples of large systems, and is suitable for the processing speed requirements of actual application scenario. Besides, feature selection method will not lead to changes in the physical meaning of the original features, thus making the it suitable for system scheduling and operation rules formulation.

According to whether the classification criterion and classification algorithm are independent of each other, the main methods of feature selection algorithm can be divided into three categories: Filter method, Wrapper method and Embedded method. The two-stage feature selection includes Filter and Wrapper methods to balance calculation efficiency and accuracy.

Filter method aims at quickly reducing the original feature space under a given criterion. It focuses primarily on the relevance between features and the target. Also, the divergence of the feature itself is usually taken into consideration for fast judgement. Filter method requires much less computing power, so it is quite suitable for the preliminary feature selection for the large-scale system machine learning process like TSA. However, the selection result depends mainly on the building of criterion.

Wrapper method, on the other side, chooses the performance of certain classifier as the main evaluation score. As the behaviour of tested features under the framework of the specific intelligent algorithm is calculated each time, it is common to take more time and computing resources to fulfil Wrapper method. Therefore, Wrapper method usually comes after Filter method because it sacrifices processing speed in exchange for accuracy of feature selection results.

3.2 Interaction gain

Interaction gain is based on information entropy as an effective measure for both effectiveness and combination effects of certain feature subset. Inspired by thermal entropy, Shannon proposed information entropy to measure abstract concept of information. Entropy measures the degree of uncertainty of a random variable as more information is needed to determine the distribution if entropy of the variable is higher.

For continuous random variables, the information entropy needs to be calculated by the integral method of probability density distribution as follows:

$$H(X) = -\int p(x)\log_2(p(x)) \quad (1)$$

Where p(x) is the probability distribution of X and H(x) is the information entropy of X.

To describe the information of multiple random variables, joint information entropy is introduced to determine the degree of uncertainty faced by multiple variables at the same time. The information entropy of two variables can be calculated as follows:

$$H(X,Y) = -\sum_{x\in X}\sum_{y\in Y} p(x,y)\log_2(p(x,y)) \quad (2)$$

Where p(x,y) is the joint probability distribution of X and Y and H(x,y) is the joint information entropy of the two variables.

Therefore,

$$H(X,Y) \geq \max(H(X), H(Y)) \quad (3)$$

It shows that the joint information entropy of the two variables is greater than the sum of the information entropy of a single variable and that conforms with the physical meaning of multivariate uncertainty. Joint information entropy is highly important for determining correlation between features and category attributes, and the calculation of redundancy between features.

Mutual information is generally used to describe the amount of information shared between two variables. It can be understood as the closeness of the mutual dependence between two random variables. Mutual information is calculated as follows:

$$MI(X;Y) = -\sum_{x\in X}\sum_{y\in Y} p(x,y)\log_2\frac{p(x,y)}{p(x)p(y)} \quad (4)$$

Where MI(X;Y) is the mutual information of X and Y.

There is a multi-value problem in the actual application of mutual information indicators, because different data ranges will affect the results of mutual comparison of multiple features. For this reason NMI is introduced as the standardized definition of mutual information. It can improve the performance of this indicator and is also recorded as symmetric uncertainty. Its definition is as follows:

$$NMI(X;Y) = \frac{2MI(X;Y)}{H(X)+H(Y)} \quad (5)$$

Where NMI(X;Y) is the symmetric uncertainty of X and Y.

As NMI focus only on the correlation between features, judgement of redundancy within feature subsets should be taken into consideration as well. So interaction gain is calculated to identify more complex complementary relationships between variables and it involves the calculation of joint entropy of multiple variables. IG is calculated as follows:

$$IG(X;Y;Z) = MI(X,Y;Z) - MI(X;Z) - MI(Y;Z) \quad (6)$$

Where IG(X;Y;Z) is the interaction gain of X, Y and Z.

The interaction gain IG(X;Y;Z) reflects the change of uncertainty caused by the addition of a new variable Y(X) due to the dependence of the variable X(Y) and Z, thus helping to determine whether to include another feature in terms of Z.

Similarly, the standardization version of IG is suitable for eliminating individual differences of features. NIG is calculated as follows:

$$NIG(X;Y;Z) = \frac{1}{2} + \frac{IG(X;Y;Z)}{2\times[H(X)+H(Y)]} \quad (7)$$

Where NIG(X;Y;Z) is the normalized interaction gain of X, Y and Z.

Features of power system TSA samples have high-dimensional and complex dependencies. Detailed and reasonable feature evaluation needs to comprehensively consider the correlation and complementarity between features and category attributes. Based on the above research, NMI is used to measure the degree of correlation between features, and NIG is used to calculate the synergy between features. On this basis, these two scores are weighted and matched to obtain the comprehensive score of a single feature, which is used as the evaluation criterion of the feature. The calculation is as follows:

$$\begin{aligned} w(f_i) &= NMI(f_i;C) + \\ &\frac{1}{N}\sum_{f_j\in F, f_j\neq f_i}^{|F|} \frac{NMI(f_i;C)}{NMI(f_i;C)+NMI(f_j;C)} \times Score(f_i, f_j) \quad (8) \\ Score(f_i, f_j) &= \begin{cases} NIG(f_i;f_j;C), IG(f_i;f_j;C) > 0 \\ 0, \text{ otherwise} \end{cases} \end{aligned}$$

Where fi represents the feature to be evaluated and w(fi) represents ultimate weight of fi.

Thus an effective criterion for each feature is generated. For a certain feature to get high enough score, it should both be strongly correlated with category attribute C and has good complementarity with the currently selected feature subset S.

3.3 Feature selection procedures based on IG

Based on IG and backward dropping algorithm (BDA), the two-stage feature selection method is given. Firstly, the data is input and processed, and the candidate set is initialized as the original feature. Secondly, in the Filter algorithm stage, the IG indicator is used to calculate the weight for sorting of features. In the Wrapper stage, the hybrid kernel function SVM algorithm is applied as the classifier evaluation. Feature elimination is achieved through backward iteration. Finally, the optimal feature subset S is output.

The flow char of two-stage feature selection procedures is shown in fig 1. The dotted line separates Filter method and Wrapper method.

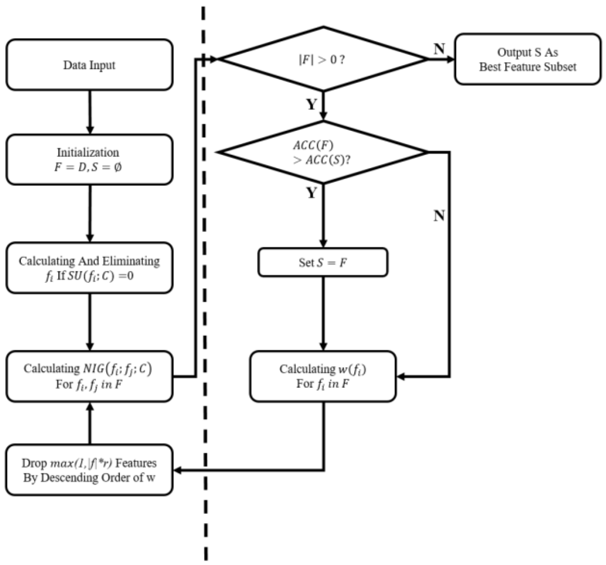

Fig 1 Feature selection procedures

4. CASE STUDY AND VISUALIZATION

4.1 Test system description

The New England 39-bus test power system is used to evaluate the effectiveness of feature selection method. This test power system model is widely used in studies and documented in the literature for TSA problems. Diagram of the test system is shown in Fig 2. This test system includes totally 39 buses, 10 generation units, 19 loads, and 46 transmission lines. The reference power is 100MVA and the reference voltage is 345kV.

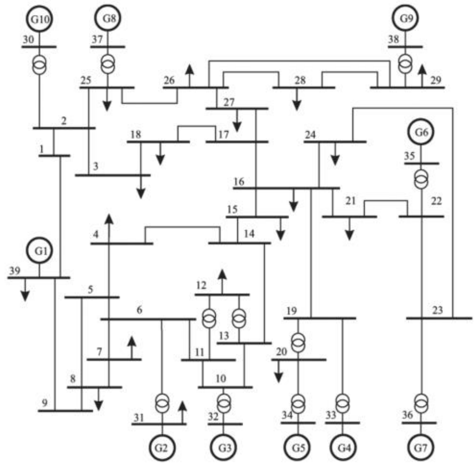

Fig 2 IEEE New England 39-bus system

4.2 Introduction

The machine learning method based on big data requires a large number of input samples for training to obtain better model performance. Therefore, this paper adopts a fixed predictive failure set to generate enough training samples. To be specific, a three-phase short-circuit ground fault is set between BUS3 and BUS4, and the line is removed after 0.15s.

In order to cover multiple operating conditions, a large number of random samples at different operating points need to be generated. Otherwise, the generalization ability of the model will be reduced because the sampling points are too close to each other. Moreover, the judgment ability of the selected features under complex situations ought to be tested. Therefore, the mass simulation generation of the samples is realized by calling the PSASP core calculation program outside its interface. Different running conditions are realized by randomly setting value of generator and load within a certain range. Cases with power flow convergence are recorded.

The power system transient stability assessment is evaluated in terms of generator rotor angles. This index is calculated using simulation results as follows:

$$\eta = \frac{360° - \Delta\delta_{\max}}{360° + \Delta\delta_{\max}} \quad (9)$$

Where $\Delta\delta_{\max}$ means the absolute value of the maximum angle of two generators at the end of the fault system. For a given sample, it is labelled “0” as stable if corresponding η is greater than 0 and “1” the otherwise.

Totally 8000 samples are generated and 5400(67.5%) among them are stable situation examples. The sample dimension is 228, if the category attribute is considered.

4.3 Algorithm validation

Since the calculation of the IG index involves the probability density function of the variable, firstly Parzen window method is used to estimate the sample result. Therefore, the function result of the probability density of a single variable and the joint probability density distribution of multiple variables are obtained.

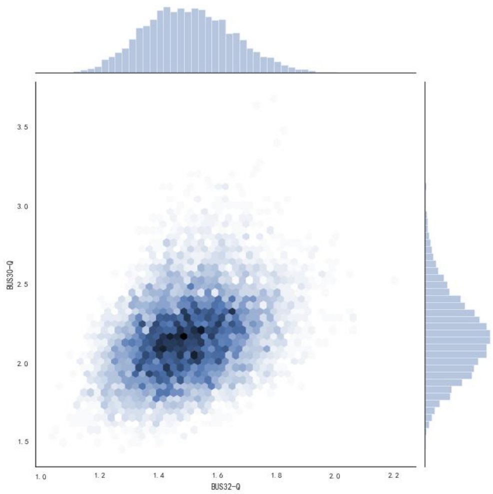

Fig 3 Joint probility density of BUS30-Q and BUS32-Q

Fig 3 shows the joint distribution probability density diagram of BUS30 and BUS32.

The estimation result fits the original data distribution well. It can smooth the peak value of sample data, and realize the calculation of related indicators of information theory.

Validation of the method is tested in two directions. The effectiveness of the two-stage feature selection method based on IG is realized by comparing it with other existing feature selection methods. The performance is measured through Accuracy(AC), False Alarms(FA) and False Dismissals(FD) that calculated as follows:

$$AC = \frac{TP + TN}{TP + FN + FP + TN} \times 100\%$$
$$FA = \frac{FN}{TP + FN + FP + TN} \times 100\% \qquad (10)$$
$$FD = \frac{FP}{TP + FN + FP + TN} \times 100\%$$

Where TN, FP, FN and TP is defined by the Confusion Matrix shown in Fig 4.

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

Fig 4 Confusion Matrix

Four types of feature selection method are considered: Interaction Gain(IG), Relief(RF), Mutual Information(MI) and Correlation Coefficient(CC). The training set remains the same and the 10-fold cross validation is applied.

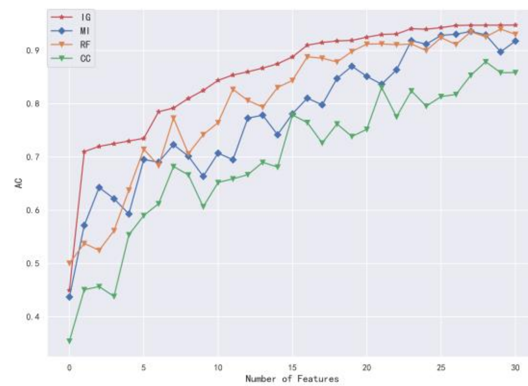

Fig 5 Accuracy results of 4 methods

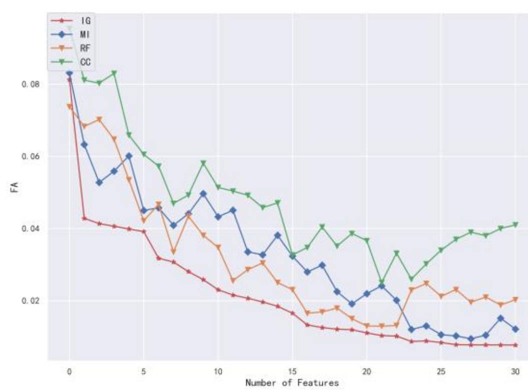

Fig 6 False Alarm results of 4 methods

Fig 6 and Fig 7 shows the number of features added for training and the corresponding AC and FA performance change curves under different methods. Firstly, the IG method proposed in this paper has the best overall performance. Secondly, the classification accuracy increases faster when the number of features in the feature subset for classification remains small. But when the number of corresponding features becomes larger, the change in classifier performance caused by adding a single feature is not significant, or even negative. In addition, the use of simple CC indicators when the number of features is large will result in serious redundancy of information and rapid deterioration of FA performance.

In terms of calculation efficiency and speed, limits of size of feature subset is removed and the total running time under the same working environment is compared. As the eventual subset represents the minimal feature set for TSA, the size of the features left is also recorded.

Feature Selection Method	AC	FA	FD	Running Time(s)	Size
IG	95.28%	0.70%	4.02%	25.08	35
MI	93.57%	1.24%	5.19%	135.10	42
RF	93.01%	2.01%	4.98%	75.36	68
CC	86.44%	4.1%	9.46%	15.15	103

Fig 8 Results of 4 different methods

Fig 8 gives the results of 4 methods. Compared with the existing, the two-stage feature selection algorithm based on IG has obvious advantages in many aspects. Although it is not as good as CC in terms of running time, its running efficiency meets the actual engineering speed requirements for pre-processing TSA problems. On the contrary, the CC index greatly loses the accuracy rate, so the obtained subset cannot be a reasonable description of the original system.

5. CONCLUSION

This paper proposes an interaction-gain-based feature selection algorithm for the power system data characteristics studied by the TSA problem. IG measures both the effectiveness and combination effects of certain feature subset, thereby simplifying the original massive feature input by modern power system. Case study on IEEE 39-bus system TSA verifies the validation in accuracy, false alarms, calculation efficiency and feature size. In the subsequent research, it is necessary to test it on real TSA sample data.

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