Retraction

Retraction: Stability analysis of distributed smart grid based on machine learning (IOP Conf. Ser.: Earth Environ. Sci. 692 022125)

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IOP Publishing has investigated in line with COPE guidelines, and during the investigation it was discovered that the article contains verbatim overlap with another work by different authors without citation [1]. As such, IOP Publishing is retracting this work.

The authors agree to this retraction.

[1] Chao Zhang et al 2021 IOP Conf. Ser.: Earth Environ. Sci. 651 022049

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Stability analysis of distributed smart grid based on machine learning

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Abstract. Decentralized Smart Grid (DSG) is a new technology proposed to power networks with elastic nodes. It can realize dynamic electricity price demand response without large-scale transformation of the infrastructure. In order to analyze the system stability of DSG, six representative machine learning classification models were applied to analyze the stability data of 10,000 samples of the 4-node system. Combined with the requirements of power system security, stability and economic performance, the effect of each classification model on the stability prediction of DSG system was tested. The test results showed that the model with a Gaussian kernel basis function kernel support Vector machine (RBF SVM) was suitable for data analysis, with the accuracy up to 97.10% and the F metric up to 0.977. CART decision tree model is suitable for real-time forecasting of power system. Under the requirement of ensuring real-time forecasting, its accuracy can reach 84.90% and F metric can reach 0.882. Its modeling and prediction calculation requirements are only 0.98% and 1.59% of that of RBF SVM model respectively.

Keywords: smart grid; Grid stability; Data mining; Machine learning.

1. Background
Decentralized Smart Grid (DSG) operates in a mode of supply and demand balance based on frequency. Smart grids with New Energy nodes are designed to be built on the basis of proper sampling of grid frequencies. The 20.2 million square meters data can effectively enhance the economy of the overall operation. As the new energy technologies represented by photovoltaic and solar energy in the power system become more and more mature, how to integrate these elastic nodes into the power [1] grid and power market and effectively maintain the stability of the system in real time has gradually become a hot issue at present. In this paper, the DSG operational data set provided by the University of California, Irvine was taken as the research object to complete the establishment of the system state model, and the stability analysis of 10,000 groups of samples in the 4-node system were conducted. In the process of analysis, six machine learning classification models are adopted to achieve the feasibility prediction of multiple indicators aiming at the tradeoff of safety, stability and economy of power system. Finally, [6] the support vector machine model which can meet the accuracy and the decision tree model which can meet the real-time requirement are obtained. Compared with the existing researches, this paper focuses more on the real time factor to complete the early warning of instability in the operation process.
2. Distributed smart grid control technology

DSG is a new kind of technology for dynamic electricity price of smart grid. The ideal electricity price strategy of traditional smart grid is to conduct electricity price auction with a cycle of 15 min, while DSG can realize dynamic demand response without large-scale transformation of infrastructure through binding electricity price and frequency rate. [9]

2.1. DSG and system model

Smart grid has certain requirements for the stable operation of the system, and the influence of elastic nodes on the stability of the system also exists in DSG system. When using traditional differential equations to describe DSG system, there are many limitations in the study of stability problem due to too many modeling constraints,[18] such as considering the fixed input problem caused by a single transformation and the problem of equal opportunity caused by too idealization. Therefore, THE SYS equation group can be used to describe the DSG system and THE SYS model were determined based on reaction time, mechanical power P, economic elasticity parameter, motor loss parameter, transmission parameter K, and system running time T. Sys model combines the physical model of the rotating motor in the system with the economic model of energy cost and derives as follows: Both the consumer node and the supplier node can be regarded as the rotating motor and follow the law of conservation of energy, i.e

\[ P_s = P_a + P_d + P_t. \]  

Where: Ps is the motor input power; Pa is the rotor mechanical power; Pd is the motor loss power; Pt is the system load power.[12] You plug in the corresponding physico-mechanical equation

\[ P_s = \frac{1}{2} M_j \frac{d^2}{dt^2}(\delta_j)^2 + \mu_j (\delta_j)^2 - \sum_k P_{j,k} \sin(\delta_k - \delta_j). \]  

When the phase angular velocity is far less than the periodic phase Angle of power frequency and the phase angular acceleration is far less than the frictional rotational potential

\[ \frac{d^2}{dt^2} = \frac{d\theta}{dt}^2 + \sum_k K_{j,k} \sin(\theta_k - \theta_j). \]  

DSG bundles the electricity charge and frequency, and allocates the elastic proportional factor CP, so that the nodes can adjust their load state through the change of electricity price. There are four response states, and the following are obtained:

\[ p_{r j} = p_{r 0} + c_p \int_{t-r_j}^{t} \frac{d\theta}{dt} (t-T_j) dt. \]

\[ \tilde{p}_{j} (p_i) = p_{i} + c_j (p_{ri} + p_{r 0}). \]

Where: PR J is the electricity price of node J; Pr d/d t = electricity price 0;P - J is the output of node J at the corresponding electricity price; Cj is the proportional coefficient of price elasticity of collocation;
J is the reaction time of power users or power producers in node J; \( T_j \) is the average time of node J, and the average frequency during this period defines the price. By combining equations (4) and (6), we can get

\[
\frac{d^2 \theta_j}{dt^2} = P_j - a_j \frac{d\theta_j}{dt} + \sum_{i=1}^{n} k_{ij} \sin(\theta_i - \theta_j) + \frac{c_{ij}}{T_j} (\theta_j(t - \tau_j) - \theta_j(t - \tau_j - T_j)).
\]  

(7)

Economic elasticity parameter \( Y_j = CP C_j \) was defined and obtained

\[
\frac{d^2 \theta_j}{dt^2} = P_j - a_j \frac{d\theta_j}{dt} + \sum_{i=1}^{n} k_{ij} \sin(\theta_i - \theta_j) + \frac{c_{ij}}{T_j} (\theta_j(t - \tau_j) - \theta_j(t - \tau_j - T_j)).
\]  

(8)

After the system node parameters are configured in accordance with the established scheme, equation (8) of DSG system is obtained, and the description of equation (1) is completed.

2.2. Criterion of system stability analysis

The local linear stability criterion was used to analyze the stability of the system. The value of SR of the root real part of system characteristic equation (1) represented whether the system was unstable: when \( SR > 0 \), the system was unstable; When \( SR < 0 \), the system remains stable. When \( SR = 0 \), it is critical state.[11]

2.3. Star DSG modeling

To sum up, a series of operation data and network stability are obtained by changing different input states of the system equation. UCI data set parameter [3] is adopted here (see table 1), and system stability data simulation model adopts 4-node star grid (as shown in figure 1).

| variable | type  | describe                       |
|----------|-------|-------------------------------|
| \( \tau \) | input | Elastic reaction time         |
| \( p \)  | input | Nodal power parameter         |
| \( \gamma \) | input | Coefficient of economic elasticity |
| \( \alpha \) | constant | Motor loss parameter        |
| \( K \)  | constant | Transmission coefficient |
| \( T \)  | constant | Pricing cycle coefficient |
| \( SR \) | output | System stability criterion    |
| \( \beta \) | output | Data set classification label |

According to the SR value, data labels were obtained, and 10,000 groups of system state vectors with output labels were finally obtained, among which 3,620 groups of positive samples lost their stability and 6,380 groups of negative samples remained stable. The body distribution was shown in Table 2, which will be used as training data for data analysis and model evaluation in the future.
Tab.2 Stability dataset of DSG

| Sample | τ1  | τ2  | τ3  | τ4  | P1  | P2  | P3  | P4  | γ1  | γ2  | γ3  | γ4  | SR  |
|--------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1      | 2.959 | 3.080 | 8.381 | 9.781 | 3.763 | -0.783 | -1.257 | -1.723 | 0.650 | 0.860 | 0.887 | 0.958 | 0.055 |
| 2      | 9.304 | 4.903 | 3.048 | 1.369 | 5.068 | -1.940 | -1.873 | 1.255 | 0.413 | 0.862 | 0.582 | 0.782 | -0.006 |
| 3      | 8.972 | 8.848 | 3.046 | 1.215 | 3.405 | -1.207 | -1.277 | -0.920 | 0.163 | 0.567 | 0.839 | 0.740 | 0.003 |
| ...    | ...  | ...  | ...  | ...  | ...  | ...  | ...  | ...  | ...  | ...  | ...  | ...  | ...  |
| 10     | 0.716 | 7.670 | 4.487 | 2.341 | 3.964 | -1.027 | -1.939 | -0.997 | 0.446 | 0.977 | 0.929 | 0.006 | 0.029 |

3. Establishment of machine learning model and evaluation index

3.1. Machine learning method for power system stability analysis

The stability of the power system is different from that of the general data set. According to the topological structure and operation state of the system, the balance of samples in the data set is quite different. In the DSG system in this paper, the proportion of positive and negative samples is about 3:7. In this paper, linear discriminant classification, Gaussian Naive Bayes (GNB) classification, K-nearest Neighbor (kNN) classification, CART decision tree (DT) classification, adaboost classification (Adaptive boosting, ADA, kernel support Vector Machine (RBF SVM), and the six algorithms basically cover the current mainstream machine learning algorithm with strong generalization ability. [17] The model optimal state with accuracy as the objective is achieved through superparameter optimization, and the algorithm performance is comprehensively evaluated by multiple indicators.

3.2. The evaluation index

The prediction results and the real situation can be expressed as a confounding matrix

\[ C = \begin{bmatrix} T_N & F_P \\ F_N & T_P \end{bmatrix} \]  

(9)

3.2.1. Index of decision accuracy – accuracy

(1) Accuracy

Accuracy is the most basic model evaluation method, accuracy (the definition symbol is \( b_{ACC} \)) is the most basic indicator to describe the model accuracy, and the calculation method is

\[ b_{ACC} = \frac{T_N + T_P}{T_N + T_P + F_P + F_N} \]

(10)

The legal range of accuracy is \([0, 1]\), and the higher the value, the better the accuracy of the mold

(2) Consistency Cohen Kappa index

In the dichotomy problem, Cohen Kappa index marker can be used to complete the accuracy assessment of the algorithm. Compared with the accuracy rate, Cohen Kappa coefficient (defined quantity symbol is \( b_{Kappa} \)) can complete the accuracy assessment of the asymmetric sample data

\[ b_{Kappa} = \frac{b_{ACC} - P_e}{1 - P_e} \]

(11)

In the formula, \( P_e = (T_N + F_P) / (T_N + F_N) + (T_P + F_N) / (T_P + F_P) \), and the legal range of Cohen Kappa coefficient is \([-1, 1]\). The higher the value, the better the accuracy of binary classification.

(3) ROC and AUC
The curve of receiver operating characteristic (ROC) positive rate and false positive rate can quantify the area under the curve as the area under curve (AUC). The AUC indicator is the relative area with a range of $[0, 1]$, and the classification model with a high AUC has better accuracy.

3.2.2. Indicators of decision propensity - sensitivity and specificity

(1) Recall and precision

Sensitivity and specificity are the concepts used to measure the decision bias, which can be measured by the recall rate (defined quantity symbol $b_R$) and the precision rate (defined quantity symbol $b_P$) respectively.

$$b_R = \frac{T_P}{T_P + F_N}, \quad b_P = \frac{T_N}{T_N + F_P}.$$  \hspace{1cm} (12)

Sensitivity and specificity represent the strict range of model decision results, and high sensitivity can be quantified as high recall rate. At this time, the model tends to make the test data decision as positive samples. High specificity can be quantified as high precision, so the model is more cautious about the decision of positive samples.\[12\]

(2) $F_\beta$ measure

$F$ metric is an index that weights and equalizes recall and precision, is the weight, usually the weight of recall, calculated as follows

$$F_\beta = \left(1 + \beta^2\right)^{-1} \left(b_R \beta + b_P \frac{1}{\beta}\right).$$  \hspace{1cm} (13)

When $\beta = 1$, $F$ measure considers that recall and precision are equally important, and the two are harmonic in average. When $\beta > 1$, the $F$ metric was considered more critical for recall, and at this point the decision bias from the highly sensitive requirements evaluation model was determined. When $0 < \beta < 1$, The $F$ metric considers precision to be more critical, and at this point the decision inclination of the model is evaluated from a highly specific need.\[6\]

3.3. Super parameter optimization and model training

The data set was divided into training set and test set according to the ratio of 7:3, the model hyperparameter training was carried out by cross validation of training set, and the configuration was 50 fold crossover. The optimization evaluation index is accuracy, and the specific method is 2-step search.\[4\] First, the random search method is used to find rough high-performance parameters in a large range, and then the grid search method is used to find the exact optimal parameters. The optimal values of optimization (super) parameters, grid optimization range and (super) parameters of each model are shown in Table 3.\[12\]

4. Performance comparison and result analysis

After super-parameter optimization was completed respectively, the pre-segmented independent test set data were substituted into the classification model, and 9 categories of measures were taken as evaluation indicators, as shown in Table 4. The confounding moment matrix of each model is completed according to the predicted data of the test set, as shown in Figure 1. Obfuscation matrix is not only an important calculation basis for the correlation of multiple parameters, but also a mapping data source of ROC curve. Several multi-angle evaluation indexes in Table 4 are obtained according to the calculation of obfuscation moment matrix. ROC curve and AUC value of each model are shown in Figure 2.
4.1. Model accuracy and consistency analysis

The accuracy of the algorithm applied to the test set is taken as the measurement standard. The performance of the six parameterized classification models is shown in Table 4 in terms of accuracy and AUC values, so that the difference in classification accuracy of each model can be more clearly compared. Among the 6 models, [13] the rBF-SVM model has the best performance, with an accuracy of about 97%, and its ROC image is most similar to the rational high-performance model, with an AUC close to 1. The accuracy of the other five models is above 80%, among which LD model has the lowest accuracy (80.47%). However, for the actual situation, the accuracy of LD model is still qualified.

Tab. 3 (Hyper) parameter optimizing and the optimal values

| model | parameter | Optimal range | The optimal value |
|-------|-----------|---------------|-------------------|
| LD    | solver    | 'svd', 'lsqr' | 'svd'             |
| KNN   | N_neighbors, Weights, metric | 1, 5, 10, …, 95, 100, uniform, 'distance', 'euclidean', 'manhattan', 'minkowski', 'chebyshev' | 30, 'distance', 'manhattan', 'chebyshev' |
| DT    | Criterion, Max depth, Min sample, leaf | 'entropy', 'gini', 1, 5, …, 100, 1, 2, …, 20 | 'gini', 30, 10 |
| ADA   | N_estimators, Learning_rate | 1, 2, …, 1000, 0.6, …, 1.5 | 850, 0.8 |
| RBF   | SVM       | C, gamma     | e^-3, e^-2, …, e^-8, e^-3, e^-2, …, e^3, 'scale' | e^3, 'scale' |
| GNB   |           |               |                   |

In this paper, and the literature [3], on the other hand, also adopted the DT model, but this article in view of the maximum depth limit of 30, DT model, and the leaf node chose a relatively large sample sizes at least 10, effectively improve the generalization performance of the model, the test results are compared with the literature [3] better, accuracy is second only to RBF SVM model. The consistency performance comparison of the 6 models is shown in Table 4, Cohen Kappa coefficient.

Tab. 4 Test dataset evaluation indicators of models

| model | accuracy | logarithmic loss | consistency index | auc | precision | recall | \(\beta=1.0\) | \(\beta=0.5\) | \(\beta=2.0\) |
|-------|----------|-----------------|-------------------|-----|-----------|--------|----------------|----------------|----------------|
| LD    | 80.47    | 0.3998          | 0.573             | 0.885 | 84.03     | 85.78  | 0.849           | 0.844           | 0.854           |
| GNB   | 82.27    | 0.3989          | 0.601             | 0.911 | 83.14     | 90.68  | 0.868           | 0.846           | 0.891           |
| KNN   | 83.00    | 0.4293          | 0.620             | 0.900 | 84.06     | 90.62  | 0.872           | 0.853           | 0.892           |
| DT    | 84.90    | 1.7557          | 0.673             | 0.902 | 88.50     | 87.81  | 0.882           | 0.884           | 0.880           |
| ADA   | 84.13    | 0.6728          | 0.652             | 0.930 | 86.61     | 88.96  | 0.878           | 0.871           | 0.885           |
| RBF   | 97.10    | 0.0828          | 0.937             | 0.996 | 98.06     | 97.40  | 0.977           | 0.979           | 0.975           |
| SVM   |          |                 |                   |      |           |        |                 |                 |                 |
According to literature [12], stability judgment results of the two models LD and GNB can be expressed as "moderate Agreement" at best. KNN, DT, and ADA can all represent "substantial agreement" for stability judgment on Cohen Kappa coefficient. SVM is the most outstanding model among several types of machine learning models. The almost Perfect Agreement can be reached. The evaluation index of comprehensive accuracy and consistency shows that all the 6 models show qualified classification accuracy. For the consistency of classification decision, they all show qualified performance except LD model. The RBF-SVM model has the best performance. Among the other 5 models, DT model has high consistency and accuracy, but the performance difference between the other models is not big. Since the unstable state is configured as a positive sample during model training, a high recall rate indicates that the system pays more attention to the unstable positive sample, that is, the system is more inclined to make fuzzy state decisions unstable. At this time, the classification model shows strong sensitivity. On the contrary, high precision indicates more attention to specificity, that is, classification models tend to make controversial state decisions stable, thus reducing the tendency of false alarm.

According to the obfuscation matrix in FIG. 2, the indexes corresponding to the recall rate and the precision rate of the modules in the test data can be obtained, as shown in Table 5 [9]. Due to its excellent accuracy, the RBF-SVM model performs well in both recall and precision and is approximately the same. The classification models with higher precision and more likely to be positive samples include DT model and ADA model. However, GNB model and kNN model have higher recall rate and are more inclined to reduce false positives of instability. Further analysis of recall and precision requires [13] to be determined using the F metric, as shown in the F metric in Table 5. When $\beta=1.0$, the harmonic mean of recall and precision is $F$ (that is, the F1 measure in the general sense).

In addition to the RBF-SVM model, the DT model has the highest $F$ (0.882) and the LD model has the worst performance (0.849). When $\beta=0.5$, the index tends to be the unstable classification model, and the DT model and ADA model have better performance. However, when $\beta=2.0$, the indicators tend to be less early-warning mode. In this case, GNB model and kNN model perform better, but compared with $\beta=0.5$, except the worst LD model (0.854) and the best RBF SVM model (0.975), the differences between the other models are relatively small. The results showed that the RBF SVM model was still the best model. DT model and ADA model tend to operate in a safer state, and try to predict the instability of the system as much as possible; GNB model and kNN model showed high sensitivity and minimized intervention to the system. LD model performance is not good.
4.2 Sensitivity and specificity analysis of the model

4.2. Model performance

See Table 5 for the comparison of calculation time between modeling and prediction of each model. It can be seen that the excellent performance of RBF-SVM model is compensated by extremely high computational cost. In terms of modeling time, ADA model, RBF-SVM model and other four types of models showed obvious differences, requiring more than 1s [12]. In terms of prediction time, ADA model and RBF-SVM model also need longer time. Longer computing time represents the need more computing power to achieve both goals, therefore, has good effect on the performance of RBF SVM model rather than GNB model or DT model more practical, this is often due to the power system stability prediction process needs to be done within 1 s, heavy classification model may not be able to meet the demand of the actual timeliness.
5. Conclusion
In this paper, by analyzing the stability data of DSG system and combining with the demand of power system safety, stability and economy, six kinds of prediction models are obtained through training optimization, and the multi-angle evaluation indexes of each model for system stability prediction are proposed. RBF SVM model is suitable for data analysis and its accuracy can reach 97.10%. DT model is suitable for real-time forecasting of power system, and its accuracy can reach 84.90%. Both adopt high sensitivity strategy to ensure the security of DSG system. In terms of computational performance, THE DT model is more excellent. Its modeling and predicted computing time are only 0.98% and 1.59% of that of the RBF-SVM model, respectively, with higher real-time performance.

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