Adaptive Load Shedding Method Based on Power Imbalance Estimated by ANN

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***Abstract*—A new adaptive load shedding method based on the artificial neural network (ANN) and power flow tracing is proposed in this paper. The ANN is used to estimate the total active power imbalance according to the time interval of frequency drop of the equivalent inertial center from the rated value to the threshold. Load frequency regulation factor and the load priority are incorporated into the power flow tracing method to choose locations of load shedding and determine the amount of load shedding of each load. The new method is tested in the 8-machine 36-bus system. The test results demonstrate that the active power imbalance estimated by the ANN is more accurate. Besides, the new load shedding algorithm can give priority to shedding the load with smaller load frequency regulation factor and protect important loads from being shed.**

Keywords—under frequency load shedding; power flow tracing; load frequency regulation factor; artificial neural network;

I. INTRODUCTION

Under frequency load shedding (UFLS) is the last control action to protect the power grid from the frequency collapse [1]. The traditional UFLS scheme cannot shed optimal amounts of loads in optimal locations in different contingencies [2]. With the development of wide area measurement system (WAMS), more timely and accurate data of the power system are available, supporting new adaptive algorithms for load shedding [3]-[5].

An adaptive load shedding algorithm based on the power flow tracing method is proposed in [6], which uses the frequency deviation and the result of power flow tracing to calculate the proportion of load shedding. The generator swing equation is used to estimate the power imbalance in [6] and [7] to help achieve adaptive load shedding.

There are some weaknesses of the power imbalance estimation by the generator swing equation. On the one hand, some sudden large power imbalance can trigger electro-mechanical oscillations in the power grid and make the generator to oscillate [8]. One the other hand, the estimation of the inertia time constant will introduce additional error in the process of the estimation [8].

Besides, the existing load shedding algorithms based on the power flow tracing method do not consider the influence of the load frequency regulation factor and the load priority. However, loads will reduce the active power absorbed from the power grid according to their load frequency regulation factor, so loads with smaller load frequency regulation factor should be given priority to shedding and the important load in the power grid should be protected from being shed incorrectly.

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In this paper, we propose a new adaptive load shedding method aiming at the case of generators tripping, based on the artificial neural network (ANN) and power flow tracing. ANNs have the ability to learn the complex and nonlinear mapping relation [9]. This paper takes the time interval of frequency drop of the equivalent inertial center from the rated value to the threshold as the input variable and the total active power imbalance of the power grid as the output variable to design the ANN and uses it to estimate the power imbalance online. Power flow tracing is a simple and transparent method which can analyze the power flow from individual generators to individual loads [10]. In this paper, load frequency regulation factor is incorporated into power flow tracing to increase the load shedding proportions of loads having smaller load frequency regulation factor. Besides, a 0-1 variable is introduced to represent the impact of the load priority to protect important loads. Simulation results demonstrate that this new method can bring the system back to a new better steady state from the point of view of frequency stability and protect important loads from being shed.

II. POWER IMBALANCE ESTIMATION

A. Power Imbalance Estimation Based on the Generator Swing Equation

When reactive power sources are enough, the impact of the voltage to the active power of the load can be ignored. The power imbalance estimated by the generator swing equation can be described as [6]

$$\Delta P = \sum_{i=1}^{n1} \Delta P_{Gi} = \sum_{i=1}^{n1} \frac{2H_i S_i}{f_n} \frac{df_{Gi}}{dt} = C_1 \frac{df_c}{dt} \tag{1}$$

where ΔP is the value of the total active power shortage; $n1$ is the number of generators in the power grid; ΔP_{Gi} is the active power imbalance (MW) of the ith generator; H_i is the inertia time constant of the ith generator; S_i is the rated apparent power (MVA) of the ith generator; f_n is the rated frequency of the power grid; f_{Gi} is the frequency of the ith generator; f_c is The frequency of the equivalent inertial center of the power grid, which is defined as (2); C_1 is a constant value, which is defined as (3).

$$f_c = \frac{\sum_{i=1}^{n1} H_i S_i f_{Gi}}{\sum_{i=1}^{n1} H_i S_i} \tag{2}$$

$$C_1 = \frac{2\sum_{i=1}^{n1} H_i S_i}{f_n} \tag{3}$$

B. Power Imbalance Estimation Based on the ANN

The feedforward neural network of one hidden layer is used to estimate the active power imbalance of the power grid online in this paper. The input variable is the time interval of f_c drop from the rated value to the threshold, denoted as ΔT, and the output variable is the active power imbalance estimation of the power grid.

If the threshold of f_c is denoted as f_0, the relation between ΔT and the active power imbalance can be described as

$$C_1(f_0 - f_n) = \int_{t_0}^{t_0+\Delta T} \Delta P dt \tag{4}$$

where t_0 is any moment of the steady state. In practice, ΔT can be measured online by WAMS directly.

After the operation mode and f_0 are determined, the left side of (4) is a constant value. So, the relation between ΔT and ΔP is that ΔT will decrease as the absolute value of ΔP increases.

III. ADAPTIVE LOAD SHEDDING ALGORITHM

If the trigger frequency of the UFLS is same for all loads, according to [6], the amount of active power load to be shed of the load of the bus k, denoted as ΔP_{Lk}, is determined as

$$\Delta P_{Lk} = \Delta P \cdot \frac{P_{tracing,k}}{\sum_{j=1}^{n2} P_{tracing,j}} \tag{5}$$

where $P_{tracing,k}$ is the active power of the load of the bus k received from the tripping generators in the steady state calculated by power flow tracing; $n2$ is the number of loads in the power grid.

Although this method is effective, there are still two aspects which are ignored.

On the one hand, when calculating the proportion of load shedding, this method does not consider the impact of load frequency regulation factor. But loads with bigger load frequency regulation factor will reduce more active power absorbed from the power grid to reduce the active power imbalance of the power grid.

On the other hand, when choosing locations of load shedding, this method ignores the impact of the load priority. But important loads should be protected when UFLS is triggered.

The relation between the change of the active power of a load and the change of the frequency is usually nonlinear, but when the frequency deviation is small, it can be simplified as

$$\Delta P_k = K_{Lk} \Delta f_k \tag{6}$$

where ΔP_k is the change of the active power of the load at bus k; K_{Lk} is the coefficient of load frequency regulation factor of the load at bus k; Δf_k is the frequency deviation of the load at bus k.

When there is a power shortage, the load having bigger K_L will reduce more active power absorbed from the power grid, which is beneficial to the recovery of the frequency.

After ΔP_k is taken into consideration, the amount of active power load to be shed of the load of the bus k, denoted as $\Delta P_{Lk\text{-}f}$, is determined as

$$\Delta P_{Lk-f} = \Delta P \cdot \frac{P_{tracing,k} - K_{Lk}(f_n - f_{tri})}{\sum_{j=1}^{n2} (P_{tracing,j} - K_{Lj}(f_n - f_{tri}))} \tag{7}$$

where f_{tri} is the trigger frequency of the UFLS.

Furthermore, the 0-1 variable e_k is introduced to represent the load priority of the load at bus k. If the load at bus k is allowed to be shed, the value of e_k is set to 1. Otherwise, the value of e_k is set to 0.

So, after the load priority is taken into consideration, the amount of active power load to be shed of the load at bus k, denoted as $\Delta P_{Lk\text{-}fp}$, is determined as

$$\Delta P_{Lk-fp} = \Delta P \cdot \frac{e_k(P_{tracing,k} - K_{Lk}(f_n - f_{tri}))}{\sum_{j=1}^{n2} e_j(P_{tracing,j} - K_{Lj}(f_n - f_{tri}))} \tag{8}$$

The new adaptive load shedding method can be used online. The ANN should be trained offline according to current operation mode. When a contingency happens, the transient state data of frequency measured by WAMS are transmitted to the control center. Then f_c can be calculated through these data. Next, the active power imbalance is estimated by the ANN and the amounts of load shedding of different loads are determined. Finally, the UFLS scheme is implemented using the communication system.

IV. TEST SYSTEM AND TEST RESULTS ANALYSIS

A. Test Case

The 8-machine 36-bus system is selected as the example, whose system wiring diagram is shown in Fig. 1. The amount of total loads is 2.568GW. The load model of all loads is the static load model which ignores the impact of the voltage to the active power of the load.

B. Training Data Generation

Training data and testing data of the ANN are generated by Monte Carlo simulation and full time domain simulation. Firstly, Monte Carlo simulation is used to generate 120 stochastic breakdowns. 100 stochastic breakdowns are used as training data and 20 stochastic breakdowns are used as testing data. Then, full time domain simulation software Power System Analysis Software Package (PSASP) is used to calculate ΔT of different contingencies.

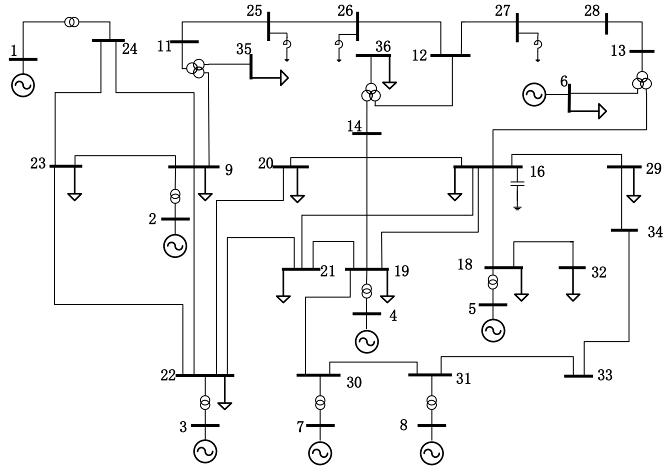

Fig. 1. System wiring diagram of the 8-machine 36-bus system

In the test case, f_n=50Hz and f_0=49.9Hz. The f_0 is obtained empirically by several tests. The scatter diagram of ΔT-ΔP relation of 120 stochastic breakdowns is shown in Fig. 2.

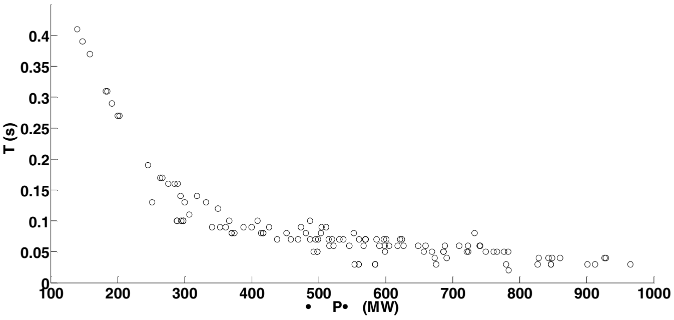

Fig. 2. Scatter diagram of ΔT-ΔP relation of 120 stochastic breakdowns

From Figure 2, the overall trend of ΔT-ΔP relation is that ΔT decreases as the absolute value of ΔP increases, which demonstrates the validity of choosing ΔT as the input variable to estimate ΔP.

C. Power Imbalance Estimation of the Test Case

TABLE I. CONFIGURATION OF THE ANN

Neurons in hidden layer	Activation function in hidden layer	Activation function in output layer	Total number of iterations
12	tansig	purelin	2000

The configuration of the ANN is given in Table I, which is obtained empirically by several tests, and the MATLAB2014 Neural Network Toolbox is used to train the ANN.

Three scenarios are selected here to test the effectiveness of the novel power imbalance estimation method.

Scenario 1 (S1): the active power imbalance of training data is estimated by the ANN.

Scenario 2 (S2): the active power imbalance of testing data is estimated by the ANN.

Scenario 3 (S3): the active power imbalance of testing data is estimated by the generator swing equation.

The mean absolute error (MAE) is used here to evaluate the effectiveness of different methods, and MAEs of different scenarios are given in Table II.

TABLE II. MAE OF THE POWER IMBALANCE ESTIMATION OF DIFFERENT SCENARIOS

Scenario	MAE (MW)
S1	63
S2	75
S3	188

From Table II, the MAEs of both S1 and S2 are smaller than S3, which demonstrates the effectiveness of the power imbalance estimation based on the ANN.

D. Load Shedding Distribution

Two scenarios are selected here to test the effectiveness of the novel load shedding algorithm.

Scenario 4 (S4): the outage of the generator of the bus 5 with 310MW and the outage of the generator of the bus 8 with 177MW in the first second are simulated. The total active power imbalance is 487MW and the load shedding scheme is designed by the method proposed in [6].

Scenario 5 (S5): the load of the bus 20 should be protected and the load shedding scheme is designed by the method proposed in this paper while other conditions are the same as scenario 4.

The K_L data of different loads in the power grid are given in Table III. In the test case, f_{tri}=49Hz. Load shedding schemes of two scenarios are given in Table IV and Table V. The active power imbalance estimation in S4 is 276.0MW, which is under-shedding, and the estimation in S5 is 531.0MW, which is over-shedding.

TABLE III. K_L DATA OF DIFFERENT LOADS IN THE POWER GRID

Bus name	K_L (MW/Hz)
22	13.6
23	17.2
29	31.2
Other load buses	0

TABLE IV. LOAD SHEDDING SCHEMES OF S4

Bus name	Amount of load drops (MW)	Proportion of load drops (%)
6	16.2	5.9
9	81.1	29.4
16	46.1	16.7
19	2.3	0.8
20	2.3	0.8
21	2.0	0.7
22	7.3	2.7
23	2.3	0.8
29	109.1	39.5
35	6.5	2.4
36	0.8	0.3
sum	276.0	100.0

TABLE V. LOAD SHEDDING SCHEMES OF S5

Bus name	Amount of load drops (MW)	Proportion of load drops (%)
6	33.5	6.3
9	168.0	31.6
16	95.6	18
19	4.8	0.9
20	0	0
21	4.2	0.8
22	5.6	1.1
23	0	0
29	204.2	38.5
35	13.4	2.5
36	1.7	0.3
sum	531.0	100.0

From the schemes given in Table IV and Table V, we can see that the power imbalance estimation of S5 is nearer to the actual value than S4, which demonstrates the effectiveness of the power imbalance estimation based on the ANN. And the load shedding proportions of the bus 22, 23 and 29 in S5 are smaller than the proportions in S4, because these three loads have bigger K_L than the loads of other buses. Besides, the method proposed in this paper is able to protect the load of the bus 20 from being shed while the method proposed in [6] does not have this ability.

The transient frequency responses of f_c of S4 and S5 are shown in Fig. 3. From Fig. 3, we can see that the load shedding scheme of S5 is able to bring the system back to a new better steady state than S4 in view of frequency stability.

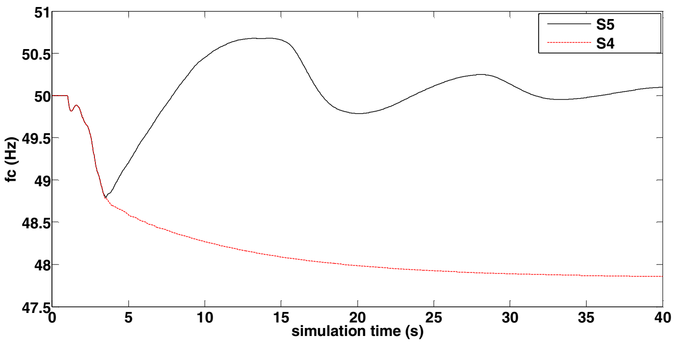

Fig. 3. Transient frequency responses of f_c of S4 and S5

Three indices are used here to evaluate the effectiveness of different methods, which are defined as follows.

The minimum dynamic f_c (MDF1).

The maximum dynamic f_c (MDF2).

The steady state f_c (SSF).

The comparison of different scenarios based on these three indices is shown in Table VI.

TABLE VI. COMPARISON OF DIFFERENT SCENARIOS

Scenario	MDF1 (Hz)	MDF2 (Hz)	SSF (Hz)
S4	47.86	50.00	47.86
S5	48.79	50.68	50.10

From Table VI, the MDF1 of S5 is higher than S4 and the SSF of S5 is nearer to the rated frequency, which demonstrate that the novel method can help the frequency recover faster and bring the system back to a better steady state in view of frequency stability. The MDF2 and SSF of S5 are higher than the rated frequency, but the extent is acceptable in practice.

V. CONCLUSION

This paper proposes a new improved adaptive load shedding algorithm based on the ANN and power flow tracing. The ANN is used to estimate the total active power imbalance according to the time interval of frequency drop of the equivalent inertial center. Load frequency regulation factor is incorporated into power flow tracing to give priority to shedding the load with smaller load frequency regulation factor. And a 0-1 variable is introduced into the algorithm to represent the load priority to protect important loads. Test results demonstrate that the accuracy of the power imbalance estimation based on the ANN is better than the estimation based on the generator swing equation and the novel load shedding algorithm can bring the system back to a new better steady state in view of frequency stability and protect the important load from being shed incorrectly.

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