### A SOLUTION CONVERGENCE IN A NEURAL NETWORK, AND AN ACCOUNTING OF LOAD PRIORITIES AT A POWER SYSTEM RESTORATION

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## ABSTRACT

Uniqueness of solution at a scheme choice for the restorable power system on the artificial neural network (ANN) base is shown. The elementary scheme of a power network is used for this purpose and the subsequent distribution of its results is applied on any network configuration. The way of priority accounting for loads is developed at creation of the restorable power system on the base of the proof on solution uniqueness for ANN.

**Keywords**: power system restoration, network configuration search, artificial neural network, load priority.

### **1. INTRODUCTION**

Power supply restoration with mode restrictions after blackouts is an important component of operational reliability for power networks [1-3]. This task is difficult for finding of an acceptable solution in the conditions of rigid time constraint because of a large number of sources, consumers and the switching devices. The use of the neural network technique together with graph processing algorithm for its solution was discussed earlier [4-6]. Such combination allows significant accelerating for a solution search, and self-training using of the artificial neural networks (ANN) expands a mode variation area.

Without stopping in details on the basic provisions [4], we want to note, the combination selection of a line breaker state for a power network, offered by ANN, is executed by the mode calculation block (MCB). It checks validity of the received combination on mode conditions and the generalized error vector, which controls ANN solution search. It is obvious; such process should not lead to a situation, when the last offered combination: a) repeats one of the previous ones, b) is situated farther of a required solution, than previous ones. The satisfaction of these constraints defines stability and convergence of the search.

On basis of back propagation algorithm for ANN training [7], it is possible to state, at the specified input data the ANN will aim to configure the weighting coefficients, to get the required response on an output, which set a difference of the current ANN

response on an output, which set a difference of the current ANN response and an error in our case [5]. Thus, for the proof of solution stability it is required to show convergence of an mismatch error for the current and required ANN responses.

#### 2. A SOLUTION CONVERGENCE

We begin the convergence proof with consideration of an elementary case for three circuits united in the triangular scheme (fig. 1). We admit there are no sources and loadings in a node  $x_3$  for simplification of situation. We construct circuit states by search method of all possible options in the mode of ANN self-training on the scheme base. Since the proof is carried out for a circuit breaker



Figure 1. The elementary cell of a power network.

state, target parameter considers the consumer providing with active power. Voltage level restrictions in nodes and currents in circuit are assigned to MCB.

Reaction of the error forming algorithm to all possible breaker state combinations for a distribution network and ANN responses to them is shown in tab. 1. HereORS – operational restrictions on breakers of a distribution network: 1 – operations are allowed with the breaker, 0 – operations are prohibited with the breaker. ANN – the breaker state is offered ANN: 1 – the breaker is switched on, 0 – the breaker is switched off. MCB – a network state is after MCB work: 1 – the breaker is switched on, 0 – the breaker is switched off. The *n*-th approximation error: 1 – the unallowable switching on because of the mode revealed by the error shaping block in MCB after its work. *X*, *Y*, *Z* – circuit breakers (fig. 1).

ANN	ORS	MCB	An error of 1-	An error of 2-	An error of 3-	Combination
XYZ	XYZ	XYZ	st approx.	nd approx.	rd approx.	#
000	000	000	000	_		0,0
000	001	000	001	—	—	0,1
000	010	000	010	—	—	0,2
000	011	000	011	—	—	0,3
000	100	000	000	—	—	0,4
000	101	000	001	100	000	0,5
000	110	000	010	100	000	0,6
000	111	000	011	000	—	0,7
001	000	000	001	000	—	1,0
001	001	001	001	000	—	1,1
001	010	000	011	000	_	1,2
001	011	001	011	000	—	1,3
001	100	000	001	000	_	1,4
001	101	001	101	000	_	1,5
001	110	000	011	100	000	1,6
001	111	001	011	000	_	1,7
010	000	000	010	000	—	2,0
010	001	000	011	000	_	2,1
010	010	010	000	_	_	2,2
010	011	010	001	000	—	2,3
010	100	000	010	000	—	2,4
010	101	000	011	000	—	2,5
010	110	010	100	000	—	2,6
010	111	010	001	000	_	2,7
011	000	000	011	000	_	3,0
011	001	001	010	000	_	3,1
011	010	010	001	000	_	3,2
011	011	011	000	_	_	3,3
011	100	000	011	000	_	3,4
011	101	001	110	000	_	3,5
011	110	010	101	000	_	3,6

Table 1. Forming stages of an error vector for all possible breaker state combinations of a network and an ANN response

continuation of table 1											
ANN	ORS	MCB	An error of 1-	An error of 2-	An error of 3-	Combination					
XYZ	XYZ	XYZ	st approx.	nd approx.	rd approx.	#					
011	111	011	000	_	_	3,7					
100	000	000	100	000	—	4,0					
100	001	000	101	000	—	4,1					
100	010	000	110	000	—	4,2					
100	011	000	111	000	—	4,3					
100	100	000	100	-	—	4,4					
100	101	000	101	100	000	4,5 (!)					
100	110	000	110	100	000	4,6 (!)					
100	111	000	111	000	-	4,7					
101	000	000	101	000	_	5,0					
101	001	001	100	000	—	5,1					
101	010	000	111	000	—	5,2					
101	011	001	110	000	—	5,3					
101	100	000	101	000	_	5,4					
101	101	101	000	_	_	5,5					
101	110	000	111	100	_	5,6 (!)					
101	111	101	000	_	_	5,7					
110	000	000	110	000	_	6,0					
110	001	000	111	000	_	6,1					
110	010	010	100	000	_	6,2					
110	011	010	101	000	_	6,3					
110	100	000	110	000	_	6,4					
110	101	000	111	100	_	6,5 (!)					
110	110	110	000	_	_	6,6					
110	111	110	000	_	_	6,7					
111	000	000	111	000	_	7,0					
111	001	001	110	000	_	7,1					
111	010	010	101	000	_	7,2					
111	011	011	100	000	_	7,3					
111	100	000	111	000	_	7,4					
111	101	101	010	000	—	7,5					
111	110	110	001	000	_	7.6					
111	111	011	100	000	_	7,7					

Since the error is equal to zero after several iterations for all considered cases, the assumption of a solution convergence for the power network scheme (fig. 1) is established. It is necessary to consider separately the cases noted by a sign "(!)". Here at the initial stage the error indicates circuit switch on, inadmissible on mode conditions. This circuit will be switched on nevertheless, but at other admissible state combination of breakers. It occurs because the error-shaping block forbids circuit switch on for the studied combination in this case because of mode restrictions, but search of the correct solution remains for ANN.

Now we will consider a case of a power network from any number of circuits, sources and consumers. Let's,  $V_k = 1$ , if a voltage isn't in the node k, and  $V_k = 0$ , if the node k is connected correctly. Function  $f_{mod}$  is determined as the sum of all nodes  $V_k$ , i.e.  $f_{mod} = \sum_{k=1}^n V_k$ , where n is number of nodes, and min $(f_{mod})$  is the sum of all  $V_k$ , which can't be provided with the electric

power in the current network configuration because of mode and other restrictions, for example, for single line that is impossible to switch on.

When the first ANN response  $(\overline{I})$  is received), it is checked by MCB, then the vector of the generalized error  $(\overline{E})$  is formed for the current response. As a result, some solution (a required response) ( $\bar{R}$ ) is formed, to which it is necessary to lead the current response, i.e.  $\bar{R} = \bar{I} - \bar{E}$ . The  $\bar{R}$ definition initializes BP algorithm. ANN weighting coefficients change so that  $\overline{I} \rightarrow \overline{R}$ . When  $\overline{I}$  will change (the state at least of one network line will change), training activity stops, a new ANN response  $\bar{I}_1$  forms  $\bar{E}_1$  and  $\bar{R}_1$ , then the training algorithm is started again. The training cycle is repeated, while  $f_{mod} > \min(f_{mod})$ .

Really when forming  $\overline{E}$  there is a continuous updating  $\overline{R}$ , until  $\overline{R}$  become a valid solution, i.e. equality will be executed  $f_{mod}(\bar{R}) = \min(f_{mod}(\bar{R}))$ . If to prove that  $f_{mod}$  constantly aims to  $\min(f_{mod})$ , it will be proved that any problem can be solved for a finite number of iterations, i.e. computation process is stable.

It is obvious from forming of an error vector algorithm [5] that only one line is considered at the same time. Let's designate it as X line from  $x_1$  top to  $x_2$  top. Then all other power network graph can simplify for forming time of an error vector for the considered line as the next ways:

1) if X line (switching on) has a available power source  $P_{\text{available}}$  (it is admissible in the  $x_1$ node), and some available / consumed power  $P_{\pm}$  is available in the  $x_3$  node, the graph is minimized



Figure 2. Scheme of network with three lines and available power in  $x_1$  node.

to presented it on fig. 2. Thus, all other network can be minimized to relative Y line, which characterizes possibility to give power from  $x_3$  to  $x_1$  (operations with Y are prohibited in the presence  $P_{\text{available.}}$  and  $P_+$ ), and to relative Z line, which considering possibility to provide the  $x_2$  loading through the  $x_3$ node, and also  $P_{\pm}$ , which can be to receive/deliver through Z or Y. Here  $P_{\pm}$  is meant that the node can be a source, a consumer or their combination.  $P_+$  and  $P_{available}$  can have both one source and different ones. Then the graph convergence of a power network is considered in tab. 1 (a combination 2, 7). If Z line is absent / is prohibited to switching on, the combination 2, 3 corresponds from tab. 1 to this case. If Y line is absent / is prohibited to switching on, the combination 2, 6 corresponds from tab. 1 to this case. If Z and Y lines are absent / are prohibited to switching on, the combination 2, 2 corresponds from tab. 1 to this case.

2) If  $P_{\text{available}}$  is in the  $x_1$  node and the  $x_2$  node is provided with the power through Z line, the network can be minimized to presented it on fig. 3. In this case Y line characterizes possibility of power transfer to the  $x_1$  or  $x_2$ nodes by a different way. It is considered in tab. 1 (a combination 4, 7). If Z line is absent / is prohibited to switching on, from tab. 1 the combination 4, 6 corresponds from tab. 1 to this case. If Y line is absent / is prohibited to switching on, from tab. 1 the combination 4, 3 corresponds from tab. 1 to this case. If Z and Y lines are absent / are prohibited to switching on, the combination 4, 2 corresponds from tab. 1 to this case.

It is obvious that two described above a case are almost identical and easily pass one in other replacement of X line by Z and vice versa, but they show in couple as ANN training will behave, when finding the best option of power transfer to the consumer, which is already provided with energy.



Figure 3. Scheme of network with available power in  $x_1$  and  $x_3$  nodes.

3) If the  $x_1$  and  $x_2$  nodes are not connected to a source, the simplified network graph corresponds to it on fig. 4 where Y line allows connecting the  $x_1$  node, and Z line allows connecting the  $x_2$  node. This case is provided to tab. 1 (a combination 0, 7). If Z line is absent / is prohibited to switching on, the combination 0, 6 corresponds from tab 1 to this case. If Y line is absent / is prohibited to switching on, the combination 0, 3 corresponds from tab. 1 to this case. If Z and Y lines are absent / are prohibited to switching on, the combination 0, 2 corresponds from tab. 1 to this case.

After forming of an error for X line  $=X_i$  the program



**Figure 4.** Scheme of network without available power in  $x_1$  and  $x_2$ 

passes to forming of an error for other lines  $X=X_k$ . There are considered the simplified network graph representations, and  $X_i$  can belong now both Y line, and Z line for new minimized graphs.

The similar is executed for all lines of the network graph then forming process of an error comes to an end, ANN training procedure is executed to change of its response. Thus, function  $f_{mod}$  changes towards reduction. The further forming procedure of the generalized error and ANN training repeats necessary number of times, until the condition  $f_{mod} = \min(f_{mod})$  will be satisfied.

Thus, it is proved that each subsequent solution does not increase the search function of combinations  $f_{mod}$ , therefore, a solution is stabile.

## **3. AN ACCOUNTING OF LOAD PRIORITIES**

The restorable generators start giving out power and gradually increase it in restoration process of power system. At equal load importance, their providing on the ANN basis is carried out according to above the stated technique. However, different consumers define requirements to load restoration urgency in different degree. In this case, operational restriction on the breaker is prohibition on its switch on (because of repair, audit, etc.). Nevertheless, it is obvious that first of all it is necessary to provide auxiliary of the generator. Generally, degree of urgency is defined by loading priority. How there is such providing for loadings?

If ANN is used, a task complexity is connected with a parallel search of the scheme for load providing. Generally, operational restriction on the breaker defines prohibition on change of the breaker state by the scheme search. Such approach allows using of ANN for load providing taking into account their priority.

If the highest priority loads are provided, the their values, the available powers in the corresponding network nodes and data on the prohibited to change of breaker states are used as basic data (here, prohibition on switch on), if those are available, and zero loadings in all other nodes. The scheme of load providing for the highest priority is defined and is remembered in the training set of the highest priority level. Further, all breakers of network which are switched on at this stage are put under restriction "prohibition on change of state". Loadings of the second priority level are added in node data, and scheme search of load providing is carried out, including the second priority level. Transition to the following priority level is made on power availability of sources after the scheme solution for level with the highest priority. The found new solution is remembered in the training set of the second priority level. These operations repeat for loadings of each priority and stop, if the available power of sources will be settled or if the level of the lowest priority is provided.

Thus, own training set is formed at each priority level, which allows putting in unambiguous compliance the basic data with the received decision, as it has been shown for case with one priority level at assessment of solution convergence on the ANN basis.

# 4. CONCLUSIONS

A power system restoration can be automated by an ANN use for increase of its reliability. It allows reducing the recovery time of a power supply especially for consumers of a high priority.

It is important to convince for network scheme search of load providing on the ANN basis that the solution is only for the proper data set. It is proved on the analysis basis of the elementary scheme and options of reduction of the network scheme to the elementary scheme that each combination of a breaker state does not repeat in the scheme search process of a network restoration, and each subsequent solution does not increase combination search function  $f_{mod}$ , therefore, a solution is stabile and converges to min $(f_{mod})$ .

For accounting of load priority in network scheme search by ANN means, it is necessary to impose condition "prohibition on the change of breaker state" for the breakers, which prohibited for switching on and for the breakers, which have connected loadings with higher priority. Own training set is formed at each priority level, which allows putting in unambiguous compliance the basic data with the received decision. The uniqueness of the solution has been proved earlier for the single priority level.

# **5. REFERENCES**

- [1] Adibi M.M., Fink L.H. Restoration after cascading failures // IEEE power & energy magazine, September/October, 2006. P. 68-77.
- [2] Barkans J., Zalostiba D. Protection against Blackouts and Self-Restoration of Power Systems / Riga, Latvija RTU Publishing House. 2009. – 142 p.
- [3] Bretas A. S., Phadke A. G. Artificial Neural Networks in Power System Restoration // IEEE Trans. on PWRD. 2003. Vol. 18. No. 4.– P. 1181-1191.
- [4] Uspensky M., Kyzrodev I. Power supply restoration in distributive networks Reliability // Theory & Applications Vol.2. No. 2, issue of June, 2011 P. 72-84.
- [5] Uspensky M., Kyzrodev I. Combined Method of a Distribution Network Reconfiguration for Power Supply Restoration // Proceeding of the IEEE PowerTech 2005, St. Petersburg, Russia, 27-30.06, Ref. 33.
- [6] Uspensky M., Smirnov S. The Occurrence Reasons and Countermeasures to Power System Blackouts // The International Journal of Energy Engineering, No. 1, 2014. P. 1-8.
- [7] Rumelhart D.E., Hinton G.E., Williams R.J. Learning integral representations by error propagation // Parallel Distributed Processing, vol. 1, No. 8, 1986. P. 318-362