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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR EXTERNAL NETWORK EQUIVALENT MODELING

SUMMARY

In this paper an artificial neural network (ANN) based methodology is proposed for determining an external network equivalent. The modified Newton-Raphson method with constant interchange of total active power between internal and external system is used for solving the load flow problem. A multilayer perceptron (MLP) with backpropagation training algorithm is applied for external network determination. The proposed methodology was tested with the IEEE 24-bus test network and simulation results show a very good performance of the ANN for external network modeling.

Key words: External Network Equivalent, Load Flow Analysis, Artificial Neural Network

1. INTRODUCTION

Power system measurement and signalization data exchange between interconnected systems still represents a significant problem for security analysis of observed power system. Inability to access needed data from the neighbouring power systems, as well as speed in processing the data to obtain satisfactory results, represent the main reasons of this. Even if the data from the neighbouring power system is accessible, considering that power systems belong to different states or countries, considerably larger problem remains the speed of obtaining the data, and achieving the simultaneity of complete data. Problem of stability and speed of

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extended real-time calculation should also be taken into consideration.

Problems associated with the acquisition of external network data, and with the influence of external network on the internal network state, are most commonly solved using the steady-state external equivalents. The most popular are static equivalents known as WARD and REI equivalents, and some of their variations [1], [2], [3]. However, they often do not give acceptable results, considering that operating and switching states of external network are often unknown and therefore have to be assumed.

More complex, and thus often more accurate methods which use unreduced models of external network [4], such as state estimation or load flow based unreduced models, have also the problem of lack of information from the external network. Because of the increase of the used data, more inaccuracies in obtained data exist, and therefore there is a greater possibility of error in load flow analysis and security assessment of power systems [5], [6].

Relatively new approach in solving the problems of power system analysis is the use of ANN's, as they have provided successful results in different fields of science. So, they present a next step forward in external network modelling [7], security analysis [8] and short-term load forecasting of power systems [9]. Well trained ANN has a potential advantage over other conventional methods of equivalencing external network in significantly improving the accuracy in pattern recognition [10]. When adequatly trained, ANN can quickly understand nonlinear relationship between input and output data, and apply the trained process online.

2. CLASSICAL METHODS OF EXTERNAL NETWORK MODELLING

2.1. External equivalent methods

There are two classical approaches of solving the problem of external network modeling for the needs of extended real-time calculation:

- the external equivalent approach,
- the external solution approach.

Application of external equivalent methods can be generally described in the following way:

a) Equivalent multipoles (branches) of external network are calculated in the boundary buses for different switching states.
b) Using the voltages in boundary buses, which are calculated using the state estimation, equivalent real-time power injections in external network are determined.

Two basic types of external network equivalents which can be gained using the afore-mentioned procedure are WARD and REI equivalent. Other methods are modified versions of these two.

Construction of WARD equivalent is based on external network data, and it is possible to represent it in two basic steps:

a) Determination of equivalent admittance (Y_{equ}) of external network using Gaussian elimination on bus admittance matrix of complete network (external network is reduced to boundary buses). Given equivalent is the same for certain switching state of external network and its different operating states.

b) Determination of additional power injections in boundary buses of WARD equivalent.

Taking into account that the power injections in the boundary buses are determined by its voltages, WARD equivalent will not give good results for the contingency analysis when an outage of internal element causes changes of those voltages. That is the reason why it is applicable, in afore-mentioned form, just for one defined switching and operating state.

Also, WARD equivalent will not give acceptable results if there are PV nodes in external network. This problem can be solved by using a modified version of basic WARD equivalent in which only the PQ nodes of external network are being reduced, and the PV nodes are kept (PV – WARD equivalent). However, for its application is necessary to know the active power and voltage magnitude in generator buses. That is why it is mostly being used for planning of transmission network. That is also a reason why a so-called extended WARD equivalent [1], [2], which can be considered a combination of basic and PV – WARD equivalent, is being used in real power systems.

Extended WARD model uses fictitious PV nodes which are added to every boundary bus to reflect the external system reactive power response to changes in the internal system. Although it gives accurate results, extended WARD equivalent is not suitable for on-line modelling of significant configuration changes of the external system since it requires all the on-line external topology information, which is very difficult to obtain.

Basic idea of REI equivalent is to concentrate all power injections from external network buses into one or more fictitious buses which are radially connected to external network. Construction of REI equivalent is possible to represent in few basic steps:

1. Power injections from external buses which are to be reduced are concentrated into fictitious node R.
2. All the boundary buses are radially connected to fictitious node G, which is connected with afore-mentioned node using the fictitious branch G – R. Admittance of the fictitious branch is determined by the power injections and voltages in the reduced buses.
3. Fictitious node G and original network buses from step 1. are eliminated.

Taking into consideration that the REI equivalent creates additional interconnections, it is preferable to use more than one equivalent. Accuracy of equivalent significantly depends on the way the external nodes are grouped into REI equivalents.

REI equivalent is considered to be suitable for contingency analysis. However, it needs to be updated constantly with information about the changes of the load and generation in the external network.

2.2. External solution methods

Application of external solution methods differs from external equivalent methods in two key elements:

- External network is analyzed in detail.

- External network data is extrapolated or assumed.

Therefore, external system is modeled entirely like internal system. Main disadvantage of this procedure is unavailability of all the necessary information. Unavailable information is most often estimated or extrapolated from internal system state information.

External network modeling based on power flow calculation can be demonstrated in few steps:

1. Switching and operating state of external system are determined based on the last accessible information from external network. Production of generators is determined by the principles of economic dispatching. Voltages in generator nodes are derived from assumed loads.
2. Bus loads are extrapolated based on the information about the internal network load and the entire network load.
3. Boundary buses are in power flow calculation treated as slack buses (voltage magnitude and angle are determined by state estimation of the internal network).
4. Difference between assumed and real external network information is noted as difference between power injections determined by internal network state estimation and calculation of power flows in external network.

External network modeling based on power flow calculation very often results in significant differences in boundary buses because the operating state of external network was not correctly assumed.

Better way for minimizing those differences is undoubtedly method based on state estimation. In fact, the goal of state estimation program is to determine, using the minimizing procedure, the most probable system state based on the measurements and signals.

In this case also, only a small number of measurements in external network is available, and the rest of the information needs to be assumed. Depending on how some information is gained, by assuming or by measurements, and also how accurate the measurements are, they are associated with a certain weight factor.

2.3. Modified Newton-Raphson method of power flow calculation

Partially modified numerical method Newton – Raphson is used for power flow calculation. Modifications of the method are necessary considering that there is another bus with regulating generator in the external network, besides the one in the internal network. In the case the inner slack bus is also a reference one, only the magnitude of voltage is known in the regulating generator bus of external network, and its voltage angle is unknown. Key information for the feasibility of the power flow calculation in that case is the interchange between two systems, which is constant and known in advance.

In *Fig 1.* is shown a simplified scheme of a network which is constituted of internal and external system. Following assumptions are made:

- Internal network has n buses altogether, of which buses marked as t_1-t_{int} are boundary buses.
- External network has m buses altogether, of which buses marked as s_1-s_{ext} are boundary buses.
- Bus marked as n is a slack bus of internal network and also a reference bus.

- Bus marked as *n+m* is a regulating generator bus of external network.
- There are g_{int} PV buses in the internal network and g_{ext} in the external network.
- PQ buses in internal network are marked with numbers $1, 2, \ldots, (n\text{-}g_{int}\text{-}1)$, and in external network with numbers $n+1, n+2, \ldots, (n+m\text{-}g_{ext}\text{-}1)$.
- PV buses in internal network are marked with numbers $(n\text{-}g_{int}), (n\text{-}g_{int}+1), \ldots, (n\text{-}1)$, and in external with numbers $(n+m\text{-}\ g_{ext}), (n+m\text{-}\ g_{ext}+1), \ldots, (n+m\text{-}1)$.
- Total interchange between two systems, marked as P_T, is constant.
- Parameters of all tie lines are known.

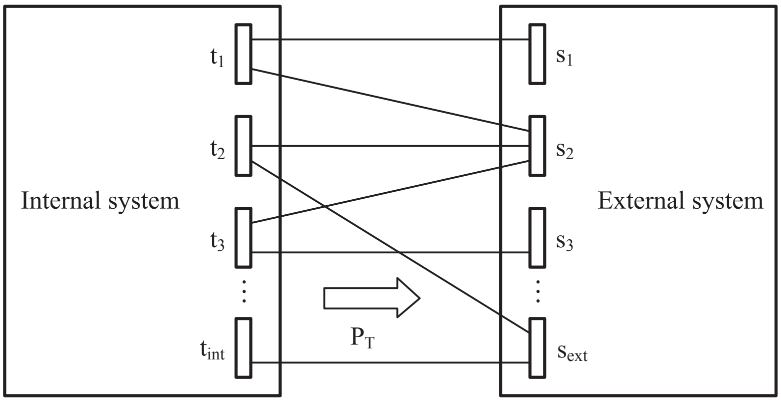

Fig. 1. Interconnected power system

As in standard Newton – Raphson method, procedure starts with assuming voltage magnitudes and angles at all PQ buses and angles at all PV buses. Voltage angle at external regulating generator bus is also assumed considering it is unknown. Assumed voltages are updated in every iteration by adding the corresponding changes to the previous values, as described in the following part.

Bus voltages are used for calculating real power injections in PV and PQ buses, and reactive power injections in PQ buses in every iteration:

$$P_{calc_i}^{(k)} = \sum_{j=1}^{n+m} \left|\vec{V}_i^{(k)}\right| \cdot \left|\vec{V}_j^{(k)}\right| \cdot \left|\vec{Y}_{ij}\right| \cdot \cos\left(\delta_i^{(k)} - \delta_j^{(k)} - \Theta_{ij}\right),\ i = 1,2,\ldots,n-1,n+1,n+2,\ldots,n+m-1 \quad (1)$$

$$Q_{calc_i}^{(k)} = \sum_{j=1}^{n+m} \left|\vec{V}_i^{(k)}\right| \cdot \left|\vec{V}_j^{(k)}\right| \cdot \left|\vec{Y}_{ij}\right| \cdot \sin\left(\delta_i^{(k)} - \delta_j^{(k)} - \Theta_{ij}\right),\ i = 1,2,\ldots,n-g_{\text{int}}-1,n+1,n+2,\ldots,n+m-g_{ext}-1 \quad (2)$$

Taking into account that the bus *n+m* with regulating generator in the external network is determined only by the magnitude of voltage, the calculation of power flow using the standard Newton-Raphson method would not be feasible. In modified Newton – Raphson method this problem is solved by adding the interchange of real power between two systems in the iterative calculation [12], because it is known in advance:

$$P_T^{(k)} = \sum_{i=1}^{int} \sum_{j=1}^{ext} \left|\vec{V}_{t_i}^{(k)}\right| \cdot \left|\vec{V}_{s_j}^{(k)}\right| \cdot \left|\vec{Y}_{t_i s_j}\right| \cdot \cos\left(\delta_{t_i}^{(k)} - \delta_{s_j}^{(k)} - \Theta_{t_i s_j}\right) \quad (3)$$

Calculated power injections in buses and interchange of real power are used to determine the mismatch vector. Elements of mismatch vector are defined as differences between specified and calculated real and reactive powers:

$$\Delta P_i^{(k)} = P_{spec_i} - P_{calc_i}^{(k)} \quad (4)$$

$$\Delta Q_i^{(k)} = Q_{spec_i} - Q_{calc_i}^{(k)} \quad (5)$$

As in standard Newton – Raphson method, aforementioned mismatch vector and the Jacobi matrix are used for calculating the correction vector. Correction vector determines values of voltage magnitude and angle for the next iteration.

Considering that the decoupled Newton – Raphson method is used, complete procedure is possible to separate into two parts using Jacobi submatrices J_1 and J_4 instead of complete Jacobi matrix:

$$\left[\Delta\delta\right]^{(k)} = \left(\left[J_1\right]^{(k)}\right)^{-1} \cdot \left[\Delta P\right]^{(k)} \tag{6}$$

$$\left[\Delta|V|\right]^{(k)} = \left(\left[J_4\right]^{(k)}\right)^{-1} \cdot \left[\Delta Q\right]^{(k)} \tag{7}$$

Because of the usage of the interchange power calculation of the Jacobi submatrices is also partially modified. Jacobi submatrix J_1 is calculated in iteration k as:

$$\left[J_1\right]^{(k)} = \begin{bmatrix} \left(\frac{\partial P_1}{\partial \delta_1}\right)^{(k)} & \cdots & \left(\frac{\partial P_1}{\partial \delta_{m+n}}\right)^{(k)} \\ \vdots & \ddots & \vdots \\ \left(\frac{\partial P_{m+n-1}}{\partial \delta_1}\right)^{(k)} & \cdots & \left(\frac{\partial P_{m+n-1}}{\partial \delta_{m+n}}\right)^{(k)} \\ \left(\frac{\partial P_T}{\partial \delta_1}\right)^{(k)} & \cdots & \left(\frac{\partial P_T}{\partial \delta_{m+n}}\right)^{(k)} \end{bmatrix} \tag{8}$$

For the feasibility of the calculation it is necessary to include partial derivation of real power interchange (P_T) with respect to bus voltage angles (δ_i, where: $i=1, 2, \dots ,n-1, n+1, n+2, \dots , n+m$) in the construction of Jacobi submatrix J_1, as it can be seen in (8).

Jacobi submatrix J_4 is calculated in iteration k as:

$$\left[J_4\right]^{(k)} = \begin{bmatrix} \left(\frac{\partial Q_1}{\partial V_1}\right)^{(k)} & \cdots & \left(\frac{\partial Q_1}{\partial V_{m+n-1}}\right)^{(k)} \\ \vdots & \ddots & \vdots \\ \left(\frac{\partial Q_{m+n-1}}{\partial V_1}\right)^{(k)} & \cdots & \left(\frac{\partial Q_{m+n-1}}{\partial V_{m+n-1}}\right)^{(k)} \end{bmatrix} \tag{9}$$

Bus voltages for iteration k+1 are calculated using the values of correction vector as:

$$\left|\vec{V}_i^{(k+1)}\right| = \left|\vec{V}_i^{(k)}\right| + \Delta\left|\vec{V}_i^{(k)}\right| \tag{10}$$

$$\delta_i^{(k+1)} = \delta_i^{(k)} + \Delta\delta_i^{(k)} \tag{11}$$

Iteration procedure stops when all the elements of mismatch vector are lower than the specified accuracy. Final results of calculation are voltage angles and magnitudes for all buses, from which is possible to determine power flows in both systems.

3. EXTERNAL NETWORK MODELING BASED ON ARTIFICIAL NEURAL NETWORKS

There are certain assumptions to be made in order for number of switching and operating states that satisfy necessary balance between power production and consumption to be reduced to number of combinations that are relevant for power system security analysis so the power system could be optimally controlled. Load flow calculation of the whole system containing internal and external power systems are the basis in defining training sets used for neural network training algorithm.

3.1. Defining training sets for neural network training algorithm

In order for training set to be produced, the following assumptions are to be taken:

1. Load changes are determined based on the known daily load curve.
2. Reactive loads in all of the external network nodes are determined considering that power factor is known for all of them.
3. Availability of power production units, transmission lines and transformers is determined according to maintenance plans.
4. Taking the hydro/thermal coordination into account as well as the principles of economic dispatching, different possibilities of production management are determined to satisfy the needed load.
5. During the load flow calculation, a satisfactory voltage and reactive power regulation is obtained through assumed voltages and transformers tap-changer positions. Extreme conditions are not taken into account, because they are not present in normal operation state.
6. The load flow calculation, used for creation of training sets, tries to keep the arranged power transfer between the power systems within the agreed limits.

Next step in neural network implementation is the choice of input and output data for training. Consequently, most important variables describing interconnected power systems are to be chosen. Every power system and its external network equivalent are described through its topology and state vector, which contains voltages in all nodes. With this stated, one will come to conclusion that the output vector of neural network should contain the same data: topology and state vector which includes voltages in every node of external network. However, this approach would not yield positive results, because the same vector would contain continuous data (node voltages) and discontinuous data (topology states). Instead, important switching and operating states determined by sensitivity analysis and randomly chosen loads in external network may be taken as output training data. After that, node voltages in whole network can be determined using the load flow calculation. Input data is determined using the sensitivity analysis. Active power flows through interconnected transmission lines between internal and external network, and transmission lines close to them were designated as data most sensitive to changes in the external network, and therefore were used as input data for training sets.

3.2. Multilayer neural network with backpropagation training algorithm

Multilayer neural network has one input layer, one or more hidden layers and one output layer. It has three significant attributes:

1. Every neuron, basic element of neural network, contains some type of activation function. Most common used functions are logistic, tangency, hyperbolic, etc.

2. Multilayer neural network has one or more hidden layers whose purpose is to select from variety of existing hidden layers those who are important and forward them to the output layer.
3. Neurons from neighbouring layers are interconnected with weight factors, often referred to as synapses.

Multilayer neural network with backpropagation training algorithm was used in this paper. This type of neural network is characterized with double passage through the network. The first passage is forwards, when neurons are activated in particular layers on the basis of information used as input data, giving the output data as result. Then, second passage is backwards, when the weight factors between particular neurons are corrected on the basis of error calculation. Error is defined as difference between real output and expected output data. In this paper, a method of fastest gradient descent is used for error correction. With this method used, the weight factor correction is proportional to the partial derivation of the sum of n quadratic errors in n-th training example. Sigmoidal function is used as activation function, because it is commonly used for nonlinear problem solving. In addition, a learning rate η is used for ensuring sufficiently fast convergence to a response of weight factors, and acceleration factor α is used for correction of expression that defines weight factor correction.

3.3. Application of artificial neural networks for power system equivalent modeling

There is a variety of scenarios that define the behavior of external network for an operating or switching state. These scenarios can be significantly different between themselves topologically and operationally, and this can complicate and slow down training process. Very often, before applying the controlled training process, training examples are grouped into clusters. Clusters are constituted from examples whose input vectors are not significantly different between themselves and therefore every switching and operating state can be observed as a cluster.

After finishing the grouping process of all prepared examples, the training process starts. All examples used for training represent the input data vector for classification of switching states. Then, for every switching state a classification of operating states is determined. Only after finishing these two processes, a recognition process can be carried out for any combination of switching and operating states. For this methodology it is typical that the process is fragmented into several levels, and the system is composed of several neural networks [11].

After the classification of switching and operating states the training process resumes with the process of recognizing the active power flows through transmission lines of external network for every single combination of switching and operating states. Considering that this data is to be very specific, an accuracy factor is very significant.

Training process is considered finished when error taken from set of examples used for random examination of neural network parameters is minimal. Also, default accuracy factor can be observed as the training stop criterion. Accuracy factor criterion is satisfied when all neurons in output layer have satisfactory accuracy factor, for all training examples.

When training process is running, a training trend and speed must be taken into account. If training process has begun with unsatisfactory starting values of weight factors or the saturation process started too soon, training has to restart with whole new set of weight factor values. Also, if the training process has reached its local minimum, a process for abandoning the local minimum must be used, such as “simulated annealing”. If the training process is too slow, learning rate and acceleration factor must be corrected, so the process can be much faster.

Testing of trained artificial neural network is needed before using the same network for recognizing the new states. Power flows are being calculated for known input-output data that was not used for the training process. Given results are being compared with results gained by artificial neural network. If the differences between these two are within limits defined in the training process it can be stated that the artificial neural network is deciding correctly, and that it can satisfactorily reconstruct external network using the determined weight factors and measurements in internal network.

4. CONCLUSION

Instead of conventional numerical methods the ANN can be successfully used for external network modeling. The planed power generation, bus loads, line outages in external network and power interchange between internal and external network are used for learning process. Once trained, an ANN is able to make decision in negligible time, because the output is obtained by simple arithmetic operations. From this reason the ANN based methodology could replace the conventional methods for external network modeling in real time operation.

5. REFERENCES

[1] F. F. Wu, A. Monticelli, Critical Review of External Network Modelling for Online security Analysis, *Electrical Power and Energy Systems, vol.5*, no.4, October, 1983, pp. 222-235.

[2] A. Bose, Modelling of External Networks for On-Line Security Analysis, *IEEE Transactions on Power Apparatus and Systems*, *vol.PAS-103,* no.8, August 1984., pp. 2117-2125.

[3] A. Monticelli, S. Deckmann, A. Garcia, B. Stott, Real Time External Equivalents for Static Security Analysis, *IEEE Transactions on Power Apparatus and Systems, vol.PAS-98*, no.2, March/April 1979., pp. 498-508.

[4] S. Deckmann, A. Pizzolante, A. Monticelli, B. Stott, Studies on Power System Load Flow Equivalencing, *IEEE Transactions on Power Apparatus and Systems*, *vol.PAS-99,* no.6, November/December 1980., pp. 2301-2310.

[5] J. F. Dopazo, M. H. Dwarakanath, J. J. Li, A. M. Sasson, An External System Equivalent Model using Real-Time Measurements for System Security Evaluation, *IEEE Transactions on Power Apparatus and Systems, vol.PAS-96*, no.2, March/April 1977., pp. 431-446.

[6] K. L. Lo, L. J. Peng, J. F. Macqueen, A. O. Ekwue, D. T. Y. Cheng, An extended Ward Equivalent Approach for Power System Security Assessment, *Electric Power Systems Research, vol.42*, no.3, September 1997., pp. 181-188.

[7] H. H. Muller, M. J. Rider, C. A. Castro, Artificial Neural Networks for Load Flow and External Equivalents Studies, *Electric Power Systems Research, vol.80*, no.9, September 2010, pp. 1033-1041.
[8] K. Warwick, A. Ekwue, R. Aggarwal, *Artificial Intelligence Techniques in Power Systems* (The Institution of Electrical Engineers, London 1997).
[9] Z. H. Ashour, M. A. Farahat, A New Artificial Neural Network Approach With Selected Inputs for Short Term Electric Load Forecasting, *International Review of Electrical Engineering (IREE)*, *vol. 3* n. 1, February 2008, pp. 32 – 36.
[10] T. Masters, *Practical Neural Network Recipes in C++* (Academic Press, San Diego, 1993).
[11] Z. H. Ashour, S. R. Hashem, H. A. Fayed, A New Approach for Combining Neural Networks During Training for Time Series Modeling, *International Review of Electrical Engineering (IREE)*, *vol. 2* n. 1, October 2007, pp. 745 – 750.