On-Line Evaluation of Capacity and Energy Losses in Power Transmission Systems by Using Artificial Neural Networks

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Abstract— **An adaptive loss evaluation algorithm for power transmission systems is proposed in this paper. The algorithm is based on training of artificial neural networks (ANNs) using backpropagation. Due to the capability of parallel information processing of the ANNs, the proposed method is fast and yet accurate. Active and reactive powers of generators and loads, as well as the magnitudes of voltages at voltage-controlled buses are chosen as inputs to the ANN. System losses are chosen as the outputs. Training data are obtained by load flow studies, assuming that the state variables of the power system to be studied take the values uniformly distributed in the ranges of their lower & upper limits. Load flow studies for different system topologies are carried out and the results are compiled to form the training set.**

Numerical results are presented in the paper to demonstrate the effectiveness of the proposed algorithm in terms of accuracy and speed. It is concluded that the trained ANN can be utilized for both off-line simulation studies and on-line calculation of demand and energy losses. High performance has been achieved through complex mappings, modeled by the ANN, between system losses and system topologies, operating conditions and load variations.

Keywords: capacity loss, energy loss, artificial neural network, power transmission systems

I. Introduction

The importance of accurate and rapid evaluation of the capacity or demand losses (MW) and energy losses (MWh) in a power system has become more recognized recently. This can be attributed to the fact that more efficient management and operation of the system is economically desirable under today's new operating environment. A number of approximate methods for estimating transmission system losses have been proposed and used by utilities. However, high accuracy and fast speed are two conflicting requirements in a loss evaluation methodology, as more detailed modeling is necessary for more accurate evaluation. This paper presents a new approach with which satisfactory performance in terms of these two requirements can be achieved.

Power system losses include those at the various levels of transmission systems (i.e., bulk transmission, transmission and subtransmission) and in the distribution networks. Due to constant variation of the operating conditions and the complexity of power systems, accurate and rapid computations of the losses have always been a challenge to utility engineers. As has been elaborated in [1], it is desirable to operate the ever increasingly complex power systems with high efficiency. To achieve this objective, loss analysis is indispensable.

Several approximating algorithms have been in use for quite some time, though accurate calculations of these losses, especially the energy losses, seem to be impractical. Depending on the purpose of the study, different approaches emphasize different aspects of the problem. For example, to compute the losses in distribution systems, two distinct loss calculation algorithms are presented in [2] and [3] which may not be suitable for transmission systems. To determine either the energy loss or the demand loss while one of the two is known, the equivalent hours loss factor equation is used in [4]. It is noted that this method is suitable only for computing subset of losses which are a function of the customer load and, therefore, should not be used for transmission systems. In [5], an approximate system losses equation is derived based on hourly system loads and transformer losses. This method is only applicable to certain situations, as

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changes of generation, demand pattern and system topology are not directly considered in the formation of the loss equation. A hierarchical (two-levels) loss evaluation procedure is presented in [1], where accurate capacity losses can be calculated using an optimal power flow (OPF) program if elaborate computer facilities are available and approximate results can be obtained using a simplified version of the OPF approach. Energy losses are computed by integration after identifying numerous operating modes and forming the loss vs. load relationships. The more the operating modes are identified and their corresponding loss relationships formed, the more accurate the algorithm will be. On the other hand, doing so will sacrifice the speed, especially when computer resources are insufficient.

As the capacity losses of a power system are complex functions of the system configuration, generation and demand pattern, as well as the various voltage levels at which the system is operating, a more complicated mapping capability is needed to approximate these functions. It is noted that the energy loss is the integration of the capacity loss over time. As the capacity loss is changing constantly, energy loss evaluation can't be accurate unless it is done on-line. To realize the complex mapping capability on-line, parallel information processing is a necessity in an algorithm for this purpose. Artificial neural networks (ANN) have these capabilities and are suitable to model the complicated mapping relationships.

This paper presents the application of Artificial Neural Networks (ANNs) for on-line evaluation of capacity and energy losses in a power transmission network. Problem formulation and design of ANN for loss evaluation is described. Results demonstrating the performance of the proposed technique for a six-bus transmission system are also included. Further applications of the proposed technique to larger power transmission systems are also discussed.

II. Multilayer Feedforward Neural Networks

Although, a single neuron processing unit can handle simplest of pattern classification problems. Multilayer feedforward networks are needed for complex situations, such as, to classify patterns which can not be classified using hyperplanes. Appendix I describes a three-layer feedforward artificial neural network where static output-limited, linear-adder neurons are used and only feedforward connections are present [6]. With a supervised training algorithm, such a network, usually having an input layer, an output layer and at least one hidden layer, can be utilized to map input patterns onto desirable output patterns.

III. Problem Formulation

As explained in the introduction, system demand or capacity losses are distributed in a transmission system and are functions of time because system topology and operating conditions change with time. To compute the total energy loss of a power system over a time period $[t_o, t_o + T]$, it is necessary to compute the total active loss of the system at sufficient instants in that time period and then integrate the active losses over that time interval. Theoretically, capacity or demand losses can be accurately computed by

$$S_L(t) = V(t)I^*(t) = P_L(t) + jQ_L(t) \tag{1}$$

where

$V(t)$ = complex bus voltage vector; and

$I^*(t)$ = conjugate of bus injected current vector.

And the total energy loss of the system over the specific time interval T is given by

$$E_L(T) = \int_{t_o}^{t_o+T} P_L(t)dt \tag{2}$$

The active power loss (MW), $P_L(t)$, and reactive power loss (Mvar), $Q_L(t)$, can be expressed by

$$P_L(t) = f(P_g, Q_g, P_d, Q_d, V, \theta, \tau) \tag{3}$$

and

$$Q_L(t) = h(P_g, Q_g, P_d, Q_d, V, \theta, \tau) \tag{4}$$

where the subscript g and d denote generation and demand, respectively, and

P_g, Q_g = injected active (MW) and reactive (Mvar) power into the system,

P_d, Q_d = absorbed active (MW) and reactive (Mvar) power from the system,

V, θ = magnitude (p.u.) and phase angle (rad) of the bus voltage, phase angle as referred to the slack bus in the system, and

τ = a time-dependent symbolic variable, indicating different system topologies.

The variables, $P_g, Q_g, P_d, Q_d, V, \theta$, are in the form of vectors and their elements are functions of time. The elements represent the values of power and voltages at different buses in the system. The variable, t (time), is omitted in these vectors for simplicity.

To develop a fast and accurate algorithm suitable for both off-line and on-line applications to compute the demand and energy losses of a power transmission system, using metered and communicated system state variables such as generation and load, it is necessary to establish the mappings, as defined by (3) and (4), between the available state variables and the system outputs. Because the computation of demand losses is instantaneous, it is impractical to assume that the voltage magnitudes and phase angles at all buses are known at each instant the computations are being carried out. Fortunately, the voltage magnitudes at the pilot buses and the generation at each power plant are known. The load consumption at each load bus is supposed to be also known, although it is not necessary to analyze the composition of the load that may be very complex. As the energy loss of a power system over a certain time period is the integration of capacity losses, its computation by (2) should be implemented on-line.

As the use of neural networks is contemplated to evaluate the capacity losses, the input vector to the neural network will consist of the generation vectors, P_g and Q_g, the load vectors, P_d and Q_d, and the vector, V, of voltage magnitudes at pilot buses. Changes of system topology are taken into account when the training data are generated. As the voltage angle, θ, is unknown at the instant the capacity loss is computed, it is not chosen as input. The effect of its change is implicitly considered when different load flow patterns are created. The outputs of the neural network are the active and reactive power losses $[P_L(t), Q_L(t)]$. Losses in other power components of interest such as transformers can also be chosen as outputs. Let $N(\cdot)$ represent the mappings of (3) and (4), then

$$[P_L(t) \quad Q_L(t)]^T = N[x(t)] \tag{5}$$

where

$$x(t) = [P_g \quad Q_g \quad P_d \quad Q_d \quad V]^T \tag{6}$$

where the superscript T denotes transpose operation and the vector V is a subset of that in (3) and (4).

The objective is, therefore, to establish the mapping function $N(\cdot)$. This can be accomplished by designing (and training) an appropriate artificial neural network. The design procedure for such a network is described in the next section.

IV. Design of the ANN

The design process includes the following steps:

(I) Preparation of suitable training data
(ii) Selection of a suitable ANN structure
(iii) Training of the ANN
(iv) Evaluation of the trained network

It is important to appreciate that the design process is iterative. It is possible that a particular structure chosen in step (ii) may not train to a designer's satisfaction. In this situation, the structure has to changed and the ANN should be retrained. Also, the trained network may not perform satisfactorily on test data. In that situation, network structure and training data should be changed and network retrained and tested.

A. Training Patterns

The training patterns should contain necessary information to generalize the problem. The preparation of a training set includes three stages. Firstly, system parameters are collected and prepared for a load flow study. Additional information needed at this stage is the maximum & minimum load consumption at each load bus and the minimum & maximum generations at each power plant. Secondly, for different system topologies, a number of load flow studies are carried out, assuming that the state variables in (6) take values uniformly distributed in between the lower and upper limits. The results are stored in a single text file. Finally, the obtained load flow patterns are normalized between [-1,1]. A sanity check procedure, which examines the feasibility of a created operating condition, is applied to check whether each load flow pattern is healthy. Impractical patterns will be removed before normalization is performed. To produce a testing set consistent to the training set, it is necessary to keep track of the normalization. The same normalizing parameters as used in the training data normalization are also used in processing the test data.

B. Structure of the Neural Network

The selection of the structure of the proposed network includes the selection of number of layers, choice of transfer function, number of inputs and number of neurons in each layer. As already mentioned, a three-layer feed-forward network can model complex mapping functions reasonably well and, therefore, is suggested for this application. A sigmoidal non-linear mapping function helps in modeling functions of arbitrary shape and is employed in this application. The number of neurons in the input layer and hidden layers are decided by experimentation which involves training and testing different network configurations. The neural network literature [7,8] provides guidelines for selecting the number of neurons for a starting network.

C. Training and Evaluation

Training of the selected network is done using training patterns and backpropagation algorithm. To achieve generalization, training and testing is interleaved. Training is stopped when the mean squared error between actual outputs and desired outputs stops improving. However, at that point, if the designer is not satisfied with the training and performance of the ANN, the training data and/or structure of the ANN are modified and the design process is repeated.

V. Application Example

The proposed approach is applied to a six-bus, 4-machine power system [9] as shown in Fig. 1. Detailed system parameters are given in [10]. To generate the training set, it is assumed that the selected input variables have the lower and upper limits as listed in Table I. As explained in Section IV, these limits are used for obtaining feasible load flow patterns. Three system topologies were used in this example for generating the training data;

Topology #1 with all seven lines in service,
Topology #2 with line 2-5 removed
Topology #3 with line 3-4 removed.

For each topology, 330 load flow studies were carried out. Then the sanity procedure was applied to the 990 load flow patterns and 935 training patterns resulted. These training patterns were considered to be sufficient because the designed network was able to achieve generalization when trained using these patterns.

An artificial neural network having three layers with n_i =15, n_h=8 and n_o=2 (as per Fig. I.1) was selected. The number of input neurons was chosen to be the same as that of the input variables. The input vector, $x(t)$, has fifteen elements for this example. Specifically, the vectors in (6) are given by

$$
\begin{aligned}
P_g &= \left[P_{g2}, P_{g3}, P_{g4}, P_{g6}\right]^T, \\
Q_g &= \left[Q_{g2}, Q_{g3}, Q_{g4}, Q_{g6}\right]^T, \\
P_d &= \left[P_{d1}, P_{d2}, P_{d5}\right]^T, \\
Q_d &= \left[Q_{d1}, Q_{d2}, Q_{d5}\right]^T, \text{ and} \\
V &= \left[V_6\right].
\end{aligned} \tag{7}
$$

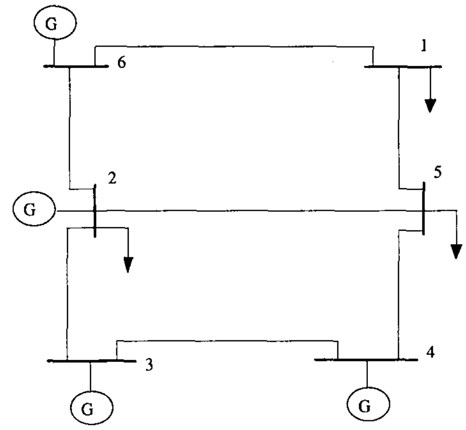

Figure 1. Single-line diagram of the example system.

After *2500* presentations of the training set to the neural network, the global error E_p was reduced to less then 2×10^{-5}, with the learning factor varying from *0.2* to *0.015* and the momentum factor being *0.3*. Then, a testing set of *300* load flow patterns which were obtained with line 1-5 removed and were not a part of the training set, was presented to the trained ANN and capacity losses were evaluated. The performance of the network was found to be very satisfactory. Table II shows the comparison of the results obtained from the ANN and load flow (LF) for the first *15* load flow patterns of the testing set. It can be seen that the computed capacity losses from the ANN are as accurate as those obtained by load flow studies.

Consider that for a time period of six hours $[t_o, t_o+6]$, load prediction and generation schedule of the system are performed using appropriate programs with a discrete time step of fifteen minutes. For each time step, the capacity loss is computed by both the ANN and the load flow (LF) program, as shown in Fig. 2. Then the active power loss is integrated:

TABLE I Lower & Upper Limits of State Variables
(Power in MW & Mvar, and Voltage in Per Unit)

Bus No	Type	Pg (min)	Pg (max)	Qg (min)	Qg (max)	Pd (min)	Pd (max)	Qd (min)	Qd (max)	V (min)	V (max)
1	1	-	-	-	-	-40	-20	-15	-5	-	-
2	1	5	15	5	10	-30	-10	-15	-5	-	-
3	1	10	40	10	25	-	-	-	-	-	-
4	1	10	30	5	15	-	-	-	-	-	-
5	1	-	-	-	-	-50	-30	-20	-10	-	-
6	3	20	50	10	30	-	-	-	-	0.9	1.1

$$E(6) = \int_{t_0}^{t_0+6} P_L(t)dt = \sum_{i=1}^{24} P_L(i) \times \Delta t_i = 624.6(MWh) \tag{8}$$

where Δt is the time step which is $15/60 = 1/4$ hour. On the other hand, the accurate energy loss computed by load flow study is *621* (MWh). The difference is only *0.5%*.

The results presented in this section indicate that the proposed ANN-based technique performs satisfactorily for the studied system and has a potential for application to other systems.

The applications of the trained ANN are twofold. For off-line simulation studies, the trained ANN can be used to predict capacity and energy losses as part of the load forecasting that is useful in system design and planning. For on-line applications, it can be used to monitor the actual capacity losses in the system provided that the state variables defined by (6) are available and to calculate the energy losses.

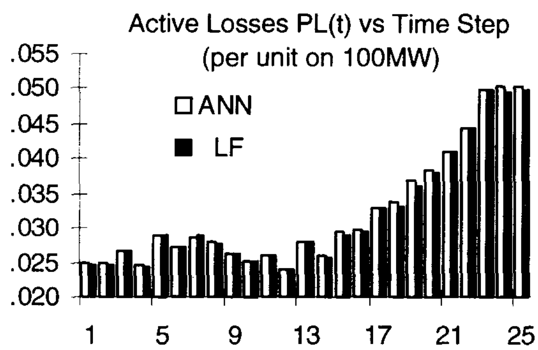

Figure 2. Comparison of active power losses as computed by the ANN and a LF program.

TABLE II: Comparison of Capacity Losses as Obtained by ANN and LF

LF	BY ANN		BY LF		ERR (%)	
CAS	PL(t)	QL(t)	PL(t)	QL(t)	P	Q
1	.0385	.1031	.0380	.1046	-1.3	1.5
2	.0338	.0806	.0332	.0808	-1.8	0.2
3	.0500	.1205	.0497	.1198	-0.4	-0.6
4	.0259	.0779	.0257	.0776	-0.9	-0.4
5	.0296	.0779	.0295	.0781	-0.5	0.2
6	.0408	.1092	.0409	.1092	0.2	0.0
7	.0249	.0648	.0247	.0645	-0.9	-0.5
8	.0249	.0698	.0247	.0693	-0.9	-0.7
9	.0369	.0930	.0362	.0943	-1.8	1.4
10	.0329	.0906	.0329	.0913	0.0	0.7
11	.0265	.0739	.0265	.0727	-0.3	-1.6
12	.0271	.0732	.0271	.0736	-0.3	0.5
13	.0287	.0876	.0288	.0884	0.3	1.0
14	.0281	.0779	.0277	.0779	-1.3	0.0
15	.0259	.0641	.0260	.0633	0.3	-1.3

VI. Future Work

The primary purpose of this paper is to present and illustrate the concept of using artificial neural networks for on-line evaluation of capacity and energy losses in a power transmission network. Most of the computations are performed off-line and involve training of the neural network for determining the appropriate weights and thresholds. On-line calculations only include forward execution of the trained network by using metered data from the transmission network which is supposed to be communicated to the system control center. The proposed concept has been demonstrated by applying it to an example power system. Future work will include the application of the proposed concept to a larger power transmission system. One of objectives will be to devise ways of reducing the number of inputs. One way of accomplishing this can be the use of only pertinent input quantities that affect the losses significantly. Another possible way can be to combine a number of input quantities into one single variable and then train the neural network. In other words, some kind of pre-processing of input quantities may be needed so that the size of the neural network is reduced. Also, the number of outputs from the neural network can also be more than two so as to include other losses of interest, such as, total transformer losses and corona losses.

VII. Conclusions

An ANN-based approach for on-line estimation of demand and energy losses in power transmission systems is presented in this paper. Artificial neural networks are used and trained to capture the complex mapping relationships between system losses and system topologies, generation and load patterns as well as controlled bus voltages in a power system. Because of the capabilities of parallel information processing and generalization of the ANN, the proposed algorithm is fast and yet accurate. The new algorithm can be used for on-line computations of capacity and energy losses with the use of metered and communicated state variables. It is also a candidate for off-line simulation studies for system design and planning.

The proposed approach is illustrated in the paper by using a test power system. Test results have demonstrated that the trained ANN can accurately predict capacity losses for different system operating conditions through its generalization and adaptability capabilities. As the speed of computation using the trained ANN is very fast, it is possible to implement such trained ANN for on-line capacity and energy losses evaluation.

VIII. Acknowledgment

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IX. References

[1] Ramon Nadira, Felix F. Wu, Dominic J. Maratukulam, E.P. Weber and C.L. Thomas" Bulk Transmission System Loss Analysis," *IEEE PWRS*, Vol. 8, No. 2, 1993.

[2] David L. Flaten, "Distribution System Losses Calculated by Percent Loading," *IEEE PWRS*, Vol. 3, No. 3, August 1988.

[3] D. I. H. Sun, S. Abe, R. R. Shoults, M. S. Chen, P. Eichenberger and D. Farris, "Calculation of Energy Losses in a Distribution System," *IEEE Trans. on PAS*, Vol. PAS-99, No. 4 July/Aug 1980.

[4] M. M. Gustafson, J. S. Baylor and S.S. Mulnix, "The Equivalent Hours Loss Factors Revisited," *IEEE PWRS*, Vol. 3, No. 4, November 1988.

[5] M. M. Gustafson, J. S. Baylor, "Approximating the System Losses Equation," *IEEE PWRS*, Vol. 4, No. 3, August 1989.

[6] R. C. Eberhart and R. W. Dobbins (Editors), *Neural Network PC Tool, A Practical Guide*, Academic Press, Inc., 1990.

[7] R. P. Lippman, "An Introduction to Computing with Neural Nets," *IEEE ASSP Magzine*, April 1987, pp. 4-22.

[8] D. Hammerstrom, "Working with Neural Networks" *IEEE Spectrum*, July 1993, pp 46-53.

[9] D. J. Sobajic and Yoh-han Pao, "Artificial Neural-Net Based Dynamic Security Assessment for Electric Power Systems," *IEEE PWRS*, Vol. 4, No. 1, February 1989.

[10] A. H. El-Abiad and K. Nagapan, "Transient Stability Regions of Multimachine Power Systems," *IEEE Trans. on PAS*, Vol. PAS-85, February 1966.

APPENDIX I

Suppose that a three-layer neural network as shown in Fig. I.1 has n_i input neurons, n_h hidden neurons and n_o output neurons. If o_j^m represents the output of the *j-th* neuron in the *m -th* layer and w_{ji}^m the weight on connection joining the *i-th* neuron in the (*m - 1*)*-th* layer to the *j-th* neuron in the *m -th* layer, then

$$o_j^m = f\left[\sum_i \left(w_{ji}^m \times o_i^{m-1}\right)\right], m \geq 2 \qquad (I.1)$$

where the function f(·) can be any differentiable function. Usually the sigmoid function as defined in (I.2) is used:

$$f(x) = \frac{2.0}{1+e^{-x}} - 1.0 . \qquad (I.2)$$

This function limits the outputs o_j^m between -1.0 and 1.0. It is possible to shift the function f(·) along x-axis by adding a threshold value to the summation term of (I.1) before the function f(·) is applied.

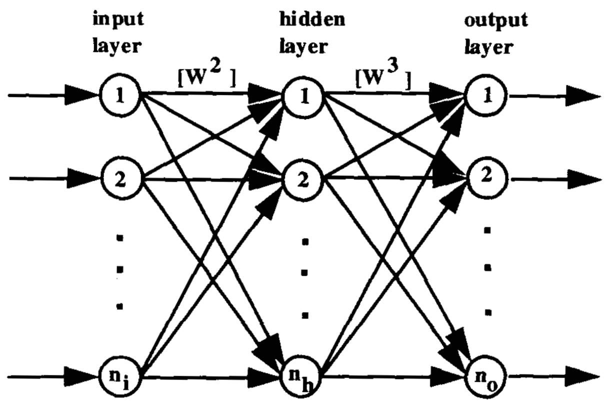

Figure I.1. A three layer feedforward ANN

To achieve the required mapping capability, the neural network is trained by repeatedly presenting a representative set of input/output patterns with backward error propagation and weight adjustment calculation to minimize the global error E_p of the network, i.e.,

$$\text{minimize} \quad E_p = \frac{1}{2} \sum_{j=1}^{n_o} \left(t_{pj} - o_{pj}^m\right)^2 \tag{I.3}$$

where t_{pj} is the target output of neuron j and o_{pj}^m is the computed output from the neural network corresponding to that neuron. Subscript p indicates that the error is considered for all the input patterns.
The minimization of this average sum-squared error is carried out over the entire training patterns. As the outputs o_{pj}^m are functions of the connection weights w^m and the outputs o_{pj}^{m-1} of the neurons in layer (m-1) which are functions of the connection weights w^{m-1}, the global error E_p is a function of w^m and w^{m-1}. The objective of training is to find the optimal connection weights w^m and w^{m-1} so that E_p will converge to a predetermined threshold value ε. Here w with superscript refers to connection matrix. A backpropagation algorithm is used in the optimization in which the weights are modified [7].

To avoid being caught a by local minima, a momentum term is used in modification of the weights. The weights and thresholds of the ANN are determined during training so that the network responds in a specified manner. The number of layers and number of neurons in each layer, as well as the values of the learning coefficient and the momentum factor are decided by experimentation. However, the number of the output neurons of the neural network for a specific application can be predetermined according to the number of output patterns.

BIOGRAPHIES

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