

Transmission and Generation Expansion Planning Considering Loadability Limit Using Game Theory & ANN

Mehdi ZareianJahromi¹, Mohammad Mehdi HosseiniBioki^{1,3}, Masoud Rashidinejad^{2,3} and Roohollah Fadaeinedjad¹

¹Department of Electrical and Computer Engineering, Kerman Graduate University of Technology, Kerman, Iran.

²Department of Electrical Engineering, Shahid Bahonar University of Kerman, Kerman, Iran.

³Iranian Association of Electrical and Electronics Engineers-Kerman Branch, Kerman, Iran.

Email: mrashidi@uk.ac.ir

Abstract— Transmission and generation expansion planning (TEP and GEP) considering loadability limit of power system is studied in this paper. Artificial neural network (ANN) technique is used to evaluate loadability limit of the power system because of its sensitivity characteristic. Power system restructuring and separation of decision-making organizations of transmission and generation expansion, make coordination between generation and transmission companies more crucial. On the other hand, voltage stability is one of the indicators of power system security level. In this paper, first the load pattern of a six-bus power system is improved and then the best bus for load increment is determined using sensitivity characteristic of ANN. Afterwards the strategic interaction between transmission company (TransCo) and generation company (GenCo) for TEP and GEP in a competitive electricity market is proposed using Game Theory (GT). The proposed algorithm comprises three optimization levels to determine Nash equilibrium such that the most profitable strategy for both sides of the game can be found out in an expansion planning game.

Keywords- Generation expansion planning , Transmission expansion planning , Game Theory, Loadability Limit and ANN.

I. INTRODUCTION

Power systems restructuring and deregulation introduces new challenges to power system planning. In a monopoly power market, decision maker is just one entity who may decide both for Generation Expansion Planning (GEP) and Transmission Expansion Planning (TEP). Due to emergence of competition in power markets, the decision makers for GEP and TEP should be separated such that the transmission company (TransCo) decides for TEP and the generation company (GenCo) decides for GEP. In such an environment, the coordination between these two entities becomes more crucial as each capacity expansion may influence the other one and as a consequence the profit of each company might be affected dependently. In a competitive power market with open access to the transmission system, the generation company is expected to supply the load without any congestion in the transmission lines. Transmission companies are obliged to provide a congestion-free, reliable and non-discriminative path from the generation companies to the consumers of electricity. Therefore, the transmission networks must be regulated so that

optimal operation is performed. In a restructured power market, the Genco decides on generation capacities, places and time of construction of new power plants at its own discretion. Under such environment, generation capacity expansion strategies taken by GenCos involve network conditions that may impose uncertainties and challenges to TEP and vice versa. On the other hand, there is no guarantee that transmission network can provide sufficient capacity for the new generation capacity constructed by the GenCo [1-5]. This interaction between Genco and TranCo leads to a new scheme of GEP & TEP that considers both entities' profit. In such an environment, Game Theory (GT) seems to be a useful method to handle a combinatorial strategy for Gencos and TransCos for generation expansion capacity and transmission expansion capacity while evaluates the power market equilibrium [6-10]. TEP and GEP have been studied separately in many researches but the interaction between two in a deregulated environment is studied in a few papers. In order to study the relationship between generation and transmission investment, a three-stage model is presented in [11]. A study in [12] shows that in a deregulated power markets, the degree of competition between different generators is dependent on the capacity of transmission lines. The interaction between transmission and generation expansion planning using Game Theory is done using a basic three-bus system in [13]. To study the strategic interaction between GenCo and TransCo, a single-stage deterministic model is proposed to in [14]. The expansion behaviors of both GenCo and TransCo can be simulated using Cournot model. The equilibrium in the power market in [14] is obtained using a Mixed Complementarity Problem (MCP) approach and the proposed model is applied to a basic three-bus system as well as an IEEE 14-bus system. On the other hand, power system security which is the ability of a power system to withstand disturbances against any violation in system operation conditions should be considered in the new method of capacity expansion, while the aforementioned studies haven't considered power system security. In this paper, first the load pattern in a six-bus power system is improved where the best bus for load increment is determined using sensitivity characteristic of ANN. Then a strategic interaction between GEP and TEP in a competitive electricity

market environment is proposed using Game Theory. It should be noted that a manageable load is assumed which can be increased or decreased using reward or penalty in a flexible manner. The paper is organized as follows: In section II, the loadability limit as a security index is introduced. The neural network used for the improvement of load pattern is presented in section III. Application of Cournot model of duopoly for TEP and GEP is discussed in section IV. Section V proposes Game Theory for solving TEP and GEP problem. A case study is presented in section VI, while conclusions are presented in section VII.

II. LOADABILITY LIMIT AS A SECURITY INDEX

In order to study the static voltage stability of the power system, loadability limit of system is proposed as voltage stability index for system security evaluation. Loadability limit of a power system is defined as the maximum load, which can be imposed on the system buses without the loss of voltage stability. In order to achieve the most appropriate load pattern to maintain power system security, the sensitivity characteristic of neural network is utilized [15-16]. The input data for training the neural network are obtained from solving the load flow.

III. BACK PROPAGATION NEURAL NETWORK

In this paper, the back propagation neural network is used for sensitivity analysis. Back propagation networks are multi-layer networks with nonlinear transfer functions. Back propagation networks are used for function estimations, finding the relations between input and output and approximation of inputs. Back propagation networks usually have one or more hidden layers of neurons with a sigmoid transfer function and the output layer is mainly linear. Fig. 1 shows the two-layer Tansig/Purelin network architecture which includes a hidden layer and an output layer with back propagation structure. This network can be used to approximate any function with a limited number of discontinuities [17].

A. Sensitivity analysis

In order to evaluate the loadability limit of the power system, sensitivity analysis is performed between the system loadability limit index and load increment pattern coefficients at each bus using the information stored in the weighting factors of the trained neural network layers. In this network, load increment pattern coefficients are considered as the inputs and loadability limit is considered as the output. The algorithm used in the proposed approach for the sensitivity analysis is shown in Fig. 2.

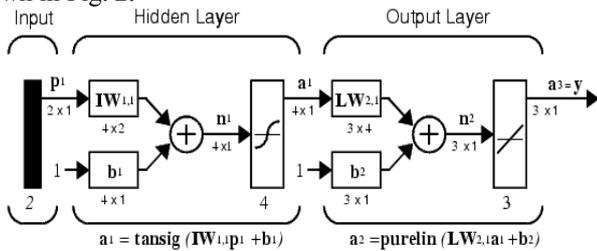


Fig. 1. The back propagation network structure

The sensitivity relationship between inputs and outputs of the neural network is expressed in (1) and the evaluation process of the loadability limit of power system by neural network is presented in Fig. 3. In order to analyze the sensitivity of the neural network outputs to the inputs, (1) is used.

$$\frac{dP_{\max}^k}{d\beta} = \frac{dP_{\max}^k}{d\sigma_k} \sum_{h=1}^{NH} W_{2kh} \frac{\partial \Psi_h}{\partial \phi_h} W_{1hj} \quad (1)$$

Where: σ_k, P_{\max}^k are input and output of the K^{th} output neuron; Ψ_h, ϕ_h are input and output of the h^{th} neuron of hidden layer; W_{2kh} is the information stored in the weighting factor connecting k^{th} output neuron to the h^{th} neuron of hidden layer; W_{1hj} is the information stored in the weighting factor connecting the h^{th} neuron of hidden layer to the j^{th} input neuron and NH is the number of neurons of hidden layer.

B. Calculation of $\frac{dP_{\max}^k}{d\sigma_k}, \frac{\partial \Psi_h}{\partial \phi_h}$

Neural network used to evaluate the loadability limit has a hidden layer and an output layer. The activation function used in the hidden layer is Sigmoid and the derivative of this function is obtained from (2):

$$f'(x) = f(x)(1-f(x)) \quad (2)$$

Where: $f(x) = \frac{1}{1 + \exp(-x)}$

Therefore:

$$\frac{\partial \Psi_h}{\partial \phi_h} = f(x_i)(1-f(x_i)) \quad (3)$$

$$x_i = \sum_{j=1}^n (\beta_j W_{ij} + b_{0i}) \quad (4)$$

Where: β_j is the matrix of the neural network inputs; W_{ij} are the weighting factors from the input layer to the hidden layer of neural network and b_{0i} are the bias values of hidden layer neurons. Activation function used in the output layer is Purelin and as the derivative of this function is equal to one, therefore $\frac{dP_{\max}^k}{d\sigma_k}$ is also constantly equal to one.

C. Preparing training patterns of neural network

In order to train the neural network, 150 training patterns are used, 100 patterns as training patterns and 50 patterns for testing the neural network. The load increment pattern coefficients are considered as inputs regardless of the load increment at the slack bus. For each load increment pattern coefficient, loadability limit is considered as the output of the neural network. Specifications of the used neural network are shown in Table I. The number of hidden neurons is determined experimentally. After deciding on the structure of ANN, it is trained by the Levenberg- Marquardt training algorithm for 62 epochs. The final error is 0.0001 in term of mean square error. Then ANN is examined by 50 unseen testing patterns with error of 0.005. After the completion of

متن کامل مقاله

دریافت فوری ←

ISIArticles

مرجع مقالات تخصصی ایران

- ✓ امکان دانلود نسخه تمام متن مقالات انگلیسی
- ✓ امکان دانلود نسخه ترجمه شده مقالات
- ✓ پذیرش سفارش ترجمه تخصصی
- ✓ امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
- ✓ امکان دانلود رایگان ۲ صفحه اول هر مقاله
- ✓ امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
- ✓ دانلود فوری مقاله پس از پرداخت آنلاین
- ✓ پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات