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Forecasting the Total Transfer Capability of Intersystem Lines for On-line Control of Electric Power System Operation

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Abstract: The paper develops a technique of total transfer capability forecasting in the controlled lines. The technique involves using dynamic state estimation, modified state estimation, and artificial neural networks. Dynamic state estimation yields the predicted values of the state variables. Modified state estimation calculates the total transfer capability on the basis of the forecast data. The obtained state is called the resultant steady state. Depending on operation constraints, the modified state estimation program parameters to be adjusted to provide optimal result of the modified state estimation are taken from the database by using ANN, and the resultant state variables of the interconnected power system are calculated. Artificial neural networks are used to quickly adjust the modified state estimator in real time.

Keywords: Measurements, dynamic state estimation, forecast, total transfer capability, electric power system.

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1. INTRODUCTION

Total Transfer Capability (TTC) is an important index for on-line control of electric power system (EPS) operation. In order to determine transfer capability of an interconnected EPS a great number of calculations are made considering various emergency situations. Out of the obtained set of transfer capability values one value is chosen by the criterion which is determined by the method of transfer capability calculation [Kulyos (2004)], [Priti Kachore (2009)], [Weixing Li (2006)], [Liang Min (2006)].

The total transfer capability is defined as the amount of electric power that can be transmitted over the interconnected transmission network in a reliable manner while meeting all of a specific set of defined pre- and post-contingency system states. The ability of interconnected transmission networks to reliably transmit electric power may be limited by the physical and electric characteristics of the systems including any one or more of the following: thermal limits, voltage limits, stability limits. The security conditions considered are the maximum line power flow, both the maximum and minimum nodal voltages.

When calculating TTC, it is necessary to consider the uncertainties and unsteady operating conditions of the EPS. Under the specified conditions, the optimal use of TTC requires that this value be forecast some time ahead. The paper proposes a technique of short-term TTC forecasting based on dynamic state estimation.

The paper is organized as follows. The second section explains a technique for TTC forecasting. The third section describes the problems of static and dynamic state estimation. The fourth section presents the information on modified state estimation and artificial neural networks. The fifth section is devoted to the on-line application of this technique. The last section presents the conclusions.

2. TECHNIQUE DESCRIPTION

The technique of TTC forecasting in the controlled lines involves using dynamic state estimation, modified state estimation, and artificial neural networks (ANN). Dynamic state estimation yields the predicted values of the state variables. Modified state estimation (MSE) calculates the total transfer capability on the basis of the forecast data. Depending on operation constraints, the MSE program parameters to be adjusted to provide optimal result of the modified state estimation are taken from the database by using ANN, and the resultant state variables of the interconnected power system are calculated. Fig.1 demonstrates a sequence of problems to be solved in a schematic form. The snapshot of measurements arrives at the control center. Then the problem of bad data detection is solved and state estimation, dynamic state estimation and modified state estimation are performed. All these problems do not depend on each other, and, therefore, are solved in parallel. The forecast data are used to solve the problem of modified state estimation. The correctness of the forecast is

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checked in the process of a comparative analysis of the forecast state variables and measurements.

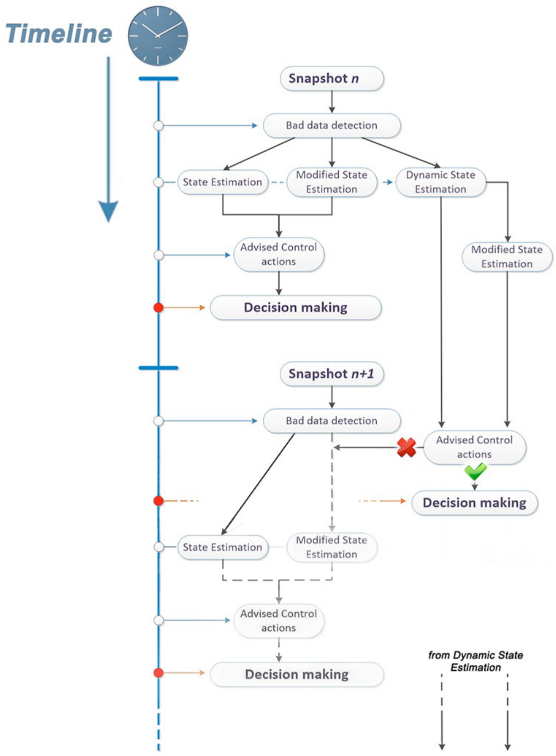

Fig. 1. A sequence of solved problems

3. THE STATE ESTIMATION PROBLEM

3.1 Static state estimation

State estimation of energy power system implies calculation of state variables, which is made on the basis of on-line information obtained from (Supervisory Control And Data Acquisition) SCADA system and WAMS (Wide-Area Measurement Systems.

The vector of measurements looks as follows:

$$\bar{y} = (U_i, \delta_i, P_{i_i}, Q_{\ i}, P_{ij}, Q_{ij_i}),$$

where $P_i = P_{l_i} + P_{g_i}$, $Q_i = Q_{g_i} + Q_{l_i}$.

U_i – magnitudes of nodal voltages; P_{g_i} ,Q_{g_i} – generation of active and reactive powers at nodes; P_{l_i} ,Q_{l_i} – loads of active and reactive powers at nodes, P_{ij} ,Q_{ij} – power flows in transformers and lines, δ_i – voltage phases at the nodes of the scheme, in which phasor measurement units (PMUs) are placed.

To solve the state estimation problem we introduce the notion of state vector $x = (\delta,\ U)$. It has a dimension $2n$, where n is the number of nodes in the calculated scheme. Such a state vector determines all the other state parameters. For steady state equations we use explicit x dependences of measured y and unmeasured z variables:

$$y = y(x), \tag{1}$$

$$z = z(x). \tag{2}$$

Equation (1) is used to determine $2n-2$ components of state vector x by measured variables and the SE problem is reduced to minimization of the criterion:

$$J(x) = (\bar{y} - y(x))^T R_y^{-1} (\bar{y} - y(x)), \tag{3}$$

i.e. to the calculation of estimates of state vector $\hat{x}$.

Newton's iterative method is used to solve the system of equations

$$(\bar{y} - y(x))^T H^T R_y^{-1} = 0 \ . \tag{4}$$

In each iteration, equations (4) are linearized at a solution point of the linear system at a previous step and the next system of linear equations is solved:

$$\Delta x = (H^T R_y^{-1} H)^{-1} H^T R_y^{-1} \Delta y, \tag{5}$$

where H – Jacobian matrix, R_y – a measurement error covariance matrix whose diagonal elements are equal to measurement variances $r_{ii} = \sigma_{yi}^2$.

Then, (2) is used to calculate the estimates of unmeasured variables.

3.2 *Dynamic State Estimation*

Dynamic state estimation takes into consideration interrelations among the time-dependent state parameters. The dynamic model applied determines largely the efficiency of dynamic state estimation. For a short-term forecasting of state parameters we use simple dynamic models

$$x_{k+1} = F_k x_k + \xi_{F(k)} \ , \tag{6}$$

where k – snapshot number. The measurements coming from SCADA system and PMU represent a sum of a true value and a normal noise

$$y = y_{true} + \xi_y \,, \ \xi_y \in N(0, \sigma_y^2 \ ),$$

where σ_y^2 – measurement variance, or

$$y_k = H_k x_k + \xi_{y(k)} \ . \tag{7}$$

In this research the extended Kalman filter is used for the dynamic state estimation. [Coutto (2009, a)], [Coutto (2009, b)], [Ning Zhou (2015)], [Hadis (2015)].

After some transformations of equations (6), (7) we can obtain a covariance matrix of forecasting errors:

$$M_{k+1} = F_k P_k F_k^T + W_{F(k)} \ . \tag{8}$$

$W_{F(k)}$ – the covariance matrix of dynamics model noise consists of $\sigma_{F(k)}^2$, P_k – covariance matrix of the state vector component estimates. The matrix of transition F is assumed to be a unit matrix because time frames considered are small enough and system changes extremely slowly.

The objective function in the dynamic state estimation looks as follows: