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A hybrid method for power system state estimation using Cellular Computational Network

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ABSTRACT

Several heuristic optimization methods including Particle Swarm Optimization (PSO) have been studied for power system state estimation and these perform quite well for small systems. However, in case of larger systems with hundreds of states, these suffer from the *curse of dimensionality*. To overcome this problem, a hybrid state estimator that consists of a Cellular Computational Network (CCN) and the Genetic Algorithm (GA) is proposed in this study. CCN is a framework that distributes the whole computation to computation cells and the cells execute local estimation. The result of CCN is further improved using GA. To compare the performance of the proposed estimator, two acclaimed variants of PSO, Comprehensive Learning PSO, and Orthogonal Learning PSO, which are specialized in multimodal high dimensional systems, are also implemented both individually and in conjunction with CCN. Through simulation, it is shown that the proposed CCN-GA outperform all direct and hybrid methods in terms of accuracy. Typical results on an IEEE 16-machine 68-bus power system are presented to illustrate the effectiveness of the CCN-GA over other methods.

1. Introduction

The main responsibility of the state estimation is to remove errors from the measurements. It is an essential tool for power systems which requires accuracy, speed, observability, scalability, robustness etc. Since its proposal in 1970 by Schweppe and Wildes (1970), Schweppe and Rom (1970) and Schweppe (1970), Weighted Least Squares (WLS) estimator is being used as the most popular tool for that purpose. Particle Swarm Optimization (PSO) aided by Genetic Algorithm (GA) is also proposed for distribution system estimation in Naka et al. (2003, 2001). PSO is also recommended for a large number of applications of power systems in Del Valle et al. (2008) and Samanta and Nataraj (2009). Very recently, the basic PSO is also proposed for transmission systems in Tungadio et al. (2015), and its effectiveness is shown for a small system of six buses with eleven states. However, the transmission systems are very large (Kekatos and Giannakis, 2013; Kantamneni et al., 2015) and the general form of PSO becomes completely unsuitable for them.

While most of the real world problems are high dimensional, most of the optimization methods suffer from getting stuck at local optima in high dimensional problems (Kuila and Jana, 2014). It is well known as the *curse of dimensionality* (Hinneburg and Keim, 1999; Rust, 1997). To recover the drawback, some variants of the basic PSO are proposed in the last decade (Imanian et al., 2014). Two of the most well acclaimed variants are the Comprehensive Learning PSO (CLPSO), and the Orthogonal Learning PSO (OLPSO). Through some random changes, these try to increase the search area of the particles and thus get out of the local optima.

A major disadvantage of the PSO based optimization is its slow convergence (Aziz and Tayarani-N, 2014). As the velocity updates are random, it becomes very slow near local optima. It seems that it requires infinite iterations to converge to the global optimal solution. Moreover, PSO is largely dependent on the starting values as well as on the choice of parameters (Lim and Isa, 2014). Due to the imperfection of the estimation, the starting values deviate from the actual values and the errors of estimation continue to flow. This harms the performance of the estimator badly.

To overcome these problems, a new framework named Cellular Computational Network (CCN) is applied for state estimation in this

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study. It was originally proposed as cellular neural networks (CNNs) in Grant and Venayagamoorthy (2009), Luitel and Venayagamoorthy (2012) and later as CCNs in Luitel and Venayagamoorthy (2014) to enhance the scalability for modeling the dynamics of large complex networks. It is first applied for power system static state estimation in Rahman and Venayagamoorthy (2015). CCN divides the whole system in small cells and completes local estimation. Then, the cells exchange and update their estimation results to get an improved result. The framework reveals some extra features which make it an independent method.

In this paper, an improved method based on CCN is compared with the PSO and the GA for estimating the states of IEEE 68-bus New York–New England (NY–NE) test system. To comply with the high dimension, CLPSO and OLPSO are also implemented for the system with 135 states. From the results, it seems that none of them can be considered as the absolute best solution which leads to the concept of hybrid estimators (Cook et al., 2000). Among the hybrids, the CCN-GA is found to perform the best regarding the accuracy. It requires a limited time to reach a specific accuracy.

The implementation of CCN based method of this study is different than that of Rahman and Venayagamoorthy (2015). In Rahman and Venayagamoorthy (2015), the whole estimation is carried out in some layer-based sequential stages. The final output comes at the end of the last layer. The computation time increases with the increase of layers. In the proposed method, all cells run simultaneously in a recursive mode based on previous estimation. As a result, the required time reduces to the execution time of only one layer. The method of Rahman and Venayagamoorthy (2015) is used for the very first sample of the current work where nothing is known about the system states. However, though it takes help from the previous estimation, the final output does not depend on it. That is why it is referred as a semi-dynamic estimator.

The main contributions of this paper are,

- A CCN based hybrid estimator is proposed to overcome of the issues of dimensionality of power system state estimation and it is shown to perform better than the existing PSO based method. It integrates GA to improve the output of the CCN.
- The general solutions of PSO for high dimension like the CLPSO, and the OLPSO are applied for state estimation for the first time. Though OLPSO improves the performance significantly, these do not completely solve the problems of the canonical PSO.
- Through simulation, direct and hybrid methods are analyzed for state estimation on the NY–NE system. Typical results are presented to illustrate the effectiveness of the proposed hybrid estimator in terms of accuracy and time.

The rest of the paper is organized as follows. The background of the WLS estimator, GA, PSO, CLPSO, and OLPSO are described in Section 2. The structural advantages of CCN are analyzed in Section 3. The experimental setup for different methods and the simulation results are discussed in Sections 4, and 5 respectively. The paper is concluded with related future works in Section 6.

2. Background

To monitor the current status of the power system, measurements are collected from different parts of the system. These are taken in the forms of power flows, power injections, voltage magnitudes, and current magnitudes etc. which contain errors of different levels. Let, $\mathbf{z}$ denotes an $m \times 1$ measurement vector including error. It is used to estimate the state vector, $\mathbf{x}$. The state vector is the set of minimum number of variables that is enough to describe the status of the whole system. All other variables can be directly calculated from the state vector (Abur and Exposito, 2004). In power system state estimation, voltage magnitudes and angles are considered as the state variables.

The angle of the reference bus is considered as the reference angle and all other angles are calculated with respect to that. If there are N buses, the state vector $\mathbf{x}$ can be represented as,

$$\mathbf{x} = [\theta_2 \ \theta_3 .. \theta_N \ V_1 \ V_2 .. V_N]^T. \tag{1}$$

Here, θ and V, with proper subscripts, represent voltage angles and magnitudes respectively. If the number of buses in the system is N, there will be $2N-1$ state variables. In case, there is no measurement of voltage magnitude, the magnitudes also become relative and the magnitude of the reference is set to 1.0. Therefore, the number of states reduces to $2N-2$. In the process of estimation, the number of measurements exceeds the number of states to form an overdetermined system.

The relation between $\mathbf{z}$, $\mathbf{x}$, and the measurement error $\mathbf{e}$ can be written as,

$$\mathbf{z} = h(\mathbf{x}) + \mathbf{e} \tag{2}$$

where, $h(.)$ denotes the nonlinear relation between the states and the measurements. For example, power flows through the transmission lines from bus i to j as well as the power injections of the buses maintain the following nonlinear relationship with the bus voltage magnitudes and angles,

$$P_{ij} = V_i^2 g_{ij} - V_i V_j g_{ij} \cos(\theta_{ij}) - V_i V_j b_{ij} \sin(\theta_{ij}) \tag{3}$$

$$Q_{ij} = -V_i^2 b_{ij} + V_i V_j b_{ij} \cos(\theta_{ij}) - V_i V_j g_{ij} \sin(\theta_{ij}) \tag{4}$$

$$P_i = V_i \sum_{j \in \mathcal{M}} V_j (G_{ij} \cos(\theta_{ij}) + B_{ij} \sin(\theta_{ij})) \tag{5}$$

$$Q_i = V_j \sum_{j \in \mathcal{M}} V_j (G_{ij} \sin(\theta_{ij}) - B_{ij} \cos(\theta_{ij})) \tag{6}$$

where, $\mathcal{M}$ represents the set of all buses connected to i, θ_{ij} represents the difference of θ_i, and θ_j, g_{ij}, and b_{ij} represent the admittance and susceptance of transmission line ij, G, and B represent the admittance and susceptance matrices respectively.

The purpose of the state estimator is to find a value $\hat{\mathbf{x}}$ that minimizes the difference between the actual value, $\mathbf{z}$ and the estimated value, $h(\hat{\mathbf{x}})$ of the measurements. As there are multiple measurements, the accuracy is measured by the L_2-norm of the differences/residues. Minimizing the norm is the objective function of the optimization problem,

$$\min_{\hat{\mathbf{x}}} \ \ \|\mathbf{z} - h(\hat{\mathbf{x}})\|. \tag{7}$$

2.1. Weighted least squares estimation

Like other nonlinear problems, WLS estimator linearizes the system over a small range. Then it applies linear operations to get an updated value. The system is linearized again based on this updated value and uses the linear estimation. This process is repeated unless the estimated value converges. In these methods, $\mathbf{x}$ is started with a close value to the solution. In the beginning, when there is no previous value, all voltage magnitudes start as 1 and all voltage angles as 0 which is known as flat start (Monticelli, 1999),

$$\mathbf{x} = [0 \ 0 ... 0 \ 1 \ 1 ... 1]^T.$$

After collecting m measurements and constructing the Jacobian matrix $\mathbf{H}(\mathbf{x})$ at flat start, in WLS estimation, the following steps are repeated until the state vector converges to a solution,

- Step 1: $\mathbf{\Delta x} = (\mathbf{H}^T \mathbf{W} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{W} (\mathbf{z} - \mathbf{h}(\mathbf{x}))$
- Step 2: $\mathbf{x}_{n+1} = \mathbf{x}_n + \mathbf{\Delta x}$
- Step 3: update $\mathbf{h}(\mathbf{x})$ with $\mathbf{x} = \mathbf{x_{n+1}}$
- Step 4: update $\mathbf{H}(\mathbf{x})$ with $\mathbf{x} = \mathbf{x_{n+1}}$.

Here, the matrix, $\mathbf{W}$ denotes the relative weights of the measurements which are usually taken as the inverse of the corresponding error variances.