Electric Power Systems Research 163 (2018) 470–481

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A multi-agent based approach to power system dynamic state estimation by considering algebraic and dynamic state variables

Sassan Goleijani*, Mohammad Taghi Ameli

Department of Electrical and Computer Engineering, Shahid Beheshti University, Tehran, Iran

ARTICLE INFO

Keywords:
Artificial neural network
Dynamic state estimation
Multi agent systems
Power system state estimation
Unscented Kalman filter

ABSTRACT

In this paper an agent-based modeling for the power system dynamic state estimation is proposed that is able to take advantages of hybrid measurement data. Multiple execution tasks are distributed among interacting agents which each agent is supposed to carry out a specific computation or functionality. The algebraic state variables of power system and the dynamic state variables of synchronous generators are considered in the proposed method. Artificial neural network is applied for deriving a parameterized process model of the algebraic state variables. The process model of the dynamic state variables is based on the fourth-order dynamic model of the synchronous generator. The dynamic state estimation problem is solved by using unscented Kalman filters. The effectiveness of the proposed method is confirmed through simulations while different scenarios are considered. The results are compared with some widely used approaches to power system dynamic state estimation. Further, since the proposed approach is benefited from agent based modeling, it is less time-consuming and can be implemented through modular configuration which is more desirable from software and hardware engineering points of view.

1. Introduction

Dynamic state estimation (DSE) was introduced to power system literature as an attempt to fulfill the need of continuous monitoring of power system [1]. The application of Phasor Measurement Units (PMU) in power system has attracted many research interests in recent years. Some research projects about the applications of real-time synchronized phasors in state estimation (SE) are listed in Ref. [2]. The applications of the PMUs in Wide Area Measurement System (WAMS) is scrutinized in Ref. [3]. Although the GPS tagged accurate data from PMUs facilitates the implementation of the power system monitoring, they may result in some difficulties in the implementation of the DSE module. For instance, SCADA usually works based on data provided by remote terminal units (RTUs) that measure electrical quantities with lower levels of accuracy in compared to the PMUs. Different sample rates of PMUs and RTUs are also another problem since it results in data gap in measurement data. Authors in Ref. [4] introduced a modified Weighted least Square (WLS)-based interpolation matrix updating strategy considering the inclusion of the real-time states of PMUs. A practical experience of implementing the forecasting-aided state estimation (FASE) is presented in Ref. [5]. The inclusion of measurement data from the PMUs in the power system DSE is also addressed in Refs. [6–9]. Despite of technical capabilities of the PMUs, it is not cost-effective to install the PMUs at all the generator terminal buses with the aim of direct measurement of generator electrical quantities, similar to the methods that is represented in some references [10–13]. Consequently, the proper approach to the DSE should be capable to handle the measurement model consists of data from RTUs and PMUs.

The Unscented Kalman filter (UKF) that is an alternative of the Kalman filter is introduced in Ref. [14] as an approach to the DSE. Since the need to linearization and calculation of Jacobian matrices are eliminated in the UKF, it has been widely used in power system DSE problems [10,15,16]. The UKF estimator is implemented for the power system DSE in Ref. [17] which comprehensive review of the benefits of the UKF over the Extended Kalman Filter (EKF) and the Weighted Least Square (WLS) method is presented. In order to enhance the numerical stability of the UKF based DSE, a new UKF method with guaranteed positive semidefinite error covariance matrix is proposed in Ref. [12]. A hybrid method proposed by [18] with the aim of taking advantages of both WLS and UKF simultaneously. In this paper, a novel approach to the power system DSE is proposed while the measurement model consists of hybrid data. Some of the concepts presented in Refs. [10,11,19] is extended to develop a practical method for real-time application. The UKF-based learning method is employed to train a dynamic neural network for (very) short term load forecasting (STLF). The output of the STLF is used to derive a parameterized process model, which is able to

* Corresponding author.
E-mail address: s_goleijani@sbu.ac.ir (S. Goleijani).

https://doi.org/10.1016/j.epsr.2018.07.019
Received 17 December 2017; Received in revised form 11 May 2018; Accepted 14 July 2018

perform continuous one-step-ahead prediction of the algebraic system variables. The fourth-order dynamic model of the synchronous generator is used in order to derive the state space model, which is solved for dynamic variables of the synchronous generators. Since the proposed estimator is able to project voltage phasors at all buses, the input data for dynamic estimation of dynamic state variables are accessible. The state estimation problems for both state space models are solved by means of the UKF. The proposed approach to the power system DSE is broken down into multiple computational tasks which are encapsulated into interacting autonomous agents. The multi agent system (MAS) comprises computing agents situated in an environment that can act autonomously in response to some changes in the environment. These agents encapsulate particular tasks or set of functionalities, in a similar way to object-oriented programming [20]. The potential applications of the MAS technology in the power system industry are addressed in Refs. [20,21]. A practical implementation of agent based modeling for tracking state estimation is reported in Refs. [22]. Authors in Ref. [23] applied MAS for distributed SE where power system is divided into several areas and each area has its own supervisory control center. In Ref. [24] the responsibility for the SE is delegated to local agents as local state estimation intelligent agents using a token that traverses the secondary substations periodically. A software-based multi-agent model using hybrid measurements from the PMUs and the RTUs is presented in [25] and a modified Cubature Kalman Filter is applied as estimator.

The main contributions of this paper, especially in relation to the authors' earlier work are as follows.

- In this paper the proposed method in Ref. [26] is extended to be applied to both algebraic and dynamic state variables of power system by considering the dynamic model of synchronous generators.
- While no discussion about the computational complexity of the power system DSE is presented in Ref. [26], this paper purposes a practical computational architecture that is based on the MAS technology.
- Unlike research papers such as Refs. [10–13], in the proposed approach there is no need to install the PMUs at all the generation buses in order to perform DSE for the dynamic state variables.

The rest of this paper is organized as follows. The derivations of the state transition models as well as the formulation of the measurement model is presented in Section 2. The proposed UKF based estimation approach is described in Section 3. The multi agent-based approach to the power system DSE is presented in Section 4. Numerical results are discussed in Sections 5 and section 6 concludes the paper.

2. Power system state transition model

Most of the researches related to the power system DSE have applied Holt's linear exponential smoothing technique for developing of state transition model of power system. Although such techniques have broad applications in estimation problems, they are not intended to be strictly accurate or reliable for every dynamic system under different situations which is a result of being model-free data-driven approaches. On the other hand, dynamics of the algebraic variables in power system is mostly driven by nodal loads. As long as there is enough information about loads and generation, complex voltages can be computed thoroughly. The interdependency between loads and complex voltages as state variables can be utilized to derive a practical model for a parametrized state transition of power system. This concept is formulated in the author's pervious work which an Artificial Neural Network (ANN) based STLF method is employed for load prediction [22]. On the other hand, there are some assumptions considered in almost all the approaches to the power system DSE that may not be applicable in practice. For instance, it is assumed that the output power and the terminal voltage of every synchronous generator in is measured by the PMUs [10,16]. The aforementioned quantities are not always accessible through direct measurement by the PMUs unless all the generator buses are equipped by the PMUs. Accordingly, we are going to use the corresponding output of the DSE carried out for the algebraic state variables as both input and measurement data at generation buses. The basis of the process model derivations is represented in the remainder of this section.

2.1. State transition model for the algebraic state variables

According to the power flow equation, injected apparent power at bus i is given by:

$$S_i = V_i \times I_i^* = P_i + jQ_i = Pg_i + jQg_i - (Pd_i + jQd_i) = V_i \times \left\{ \sum_{k=1}^{n_b} Y_{ik} \times V_k \right\}^* \tag{1}$$

where V_i and I_i are bus voltage and total injected current, P_i and Q_i are injected active and reactive power, Pg_i and Qg_i are active and reactive power generated by generation units, Pd_i and Qd_i are nodal active and reactive demand at ith bus. Nodal active and reactive demands are forecasted by the neural network and the state vector can be computed accordingly. ϕ_i is defined at each bus as follows:

$$\phi_i = |V_i| e^{j\delta_i} \times \left\{ \sum_{k=1}^{n} |Y_{ik}| \times |V| \times e^{j(\delta_k + \theta_{ik})} \right\}^* - Pg_i - jQg_i + Pd_i + jQd_i = 0 \tag{2}$$

where Y_{ik} is corresponding element of admittance matrix, θ_{ik} is the phase angle of Y_{ik} and δ_i is voltage. Let's consider,

$$\Phi = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \phi_3 \\ \vdots \\ \phi_{nb} \end{bmatrix} \tag{3}$$

The state vector is defined as:

$$x = [\overline{U} \quad \overline{\delta}] \tag{4}$$

where $\overline{U}$ and $\overline{\delta}$ are vectors of voltage magnitudes and voltage angles of power system. The forecasted demand vector is defined as:

$$L = [Pd \quad Qd] \tag{5}$$

The full derivative of Φ(x, L) reveals the following relation:

$$(\partial\Phi/\partial x)dx + (\partial\Phi/\partial \mathrm{L})dL = J \times dx + I \times dL = 0 \tag{6}$$

where I is the identity matrix and J is Jacobian matrix. The last relationship can be used to derive a discrete time transition model for state vector as per follow.

$$dx = -J^{-1} \times I \times dL = -J^{-1} \times dL \tag{7}$$

Let's assume dL represents vector of changes in nodal demands with respect τ:

$$dL(t + \tau) = L(t + \tau) - L(t) \tag{8}$$

where $L(t + \tau)$ is the forecasted demand through ANN-based and can be expressed as:

$$dL(t + \tau) = f(u(t)) - L(t) \tag{9}$$

where

$$u(t) = \begin{bmatrix} L(t) & C(t) \\ L(t-\tau) & C(t-\tau) \\ \vdots & \vdots \\ L(t-M\tau) & C(t-M\tau) \end{bmatrix} \tag{10}$$