Power System Dynamic State Estimation Using Smooth Variable Structure Filter

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***Abstract*— With the integration of distributed energy resources (DER) traditional power systems evolved toward modernized smart grids. Although smart grids open up the possibility for more reliable and secure energy management, they impose new challenges on real-time monitoring and control of the power grid. State estimation is a key function which plays a vital role in reliable system control. In this paper, the smooth variable structure filter (SVSF) is used for power system dynamic state estimation (DSE). SVSF is a predictor-corrector based approach which can be applied to both linear and nonlinear system with the ability to deal with the system uncertainties. The simulation results on a single machine with infinite bus power network shows the superiority of the proposed SVSF compared to extended Kalman filter (EKF) and unscented Kalman filter (UKF). The results of the proposed method show a significant smoothness and accuracy in its performance compared to those obtained from EKF and UKF approaches; in particular, in the presence of measurement outliers.**

Keywords—dynamic state estimation, EKF, UKF, SVSF.

I. INTRODUCTION

The electric power industry is undergoing profound changes towards more dynamic and complex structures in support of sustainable energy utilization. The integration of distributed energy resources (DER), micro-grids, aggregated demand response, and customer participation in the power market offers the unique opportunity to transform the distribution system into an active and controllable resource, however, poses new operational challenges in system monitoring and control [1], [2]. So, system operators will have to play a more active role to face the increasing variable and less predictable load profiles in the network which makes state estimation a necessary requirement for the smart grid [3], [4]. By modeling the time-varying nature of the system, state estimation alleviates losses under drastic changes during load fluctuations or network switching in smart grids, so, its accuracy and reliability will have a significant impact on the operation of the future grid.

The main goal for a state estimator is to process the data, filter measurement noise, and detect gross errors. That leads to facilitate efficient and accurate monitoring of operational conditions in the power system, which provides reliable real-time data of the power grids [5]. The state estimator functions can be summarized in five functions: Firstly, it configures on-line diagram of the system by gathering status data which is called the topology processor; secondly, the observability analysis determines the available set of measurement to figure out whether the state estimation for the power system can be achieved or not and identify the unobservable nodes. Thirdly, calculates the optimal state estimate for the power system; this function is called the state estimation solution. The fourth function is called bad data processing, which detects the gross errors in the measurement. This stage is to provide enough redundant measurement. Eventually, estimates different systemic parameters to detect the structural errors in the configuration of the grid, which characterizes the errors. This function provides the estimator whether there is enough measurement redundancy or not as well. The result of a state estimator will be inspected to classify the power grid states based on one of the three categories [6]. The three status of the power grids is Normal State, which could be safe or unsafe, Emergency State, and Restorative state. The more accurate state estimator we have, the better operational condition of the system we will get.

There are two main types of state estimation in the power system: the static state estimation (SSE) and dynamic state estimation (DSE). The SSE depends on conventional computations techniques like estimation, detection, statistics, and filtering [7]. Along with SSE, the DSE deals with the current and previous state of the power system beside the knowledge of the physical model of the system in order to estimate the state vector for the next time. This technique gives the electricity provider a specific time to act in term of emergent physical events or bad data injection[8], [9]. The DSE has been chosen to be implemented in this paper. The single-machine-infinite-bus is chosen as the tested system.

The state estimation method has been widely applied by using different methods. The most common method being applied in the power system is the weighted least square method (WLS), which relies on minimizing the total squares of the weighted deviations from the real measurement of the predicted states [10], [11]. Another method in the power system state estimation is Kalman filters; theoretically, the Kalman filter's iteration is based on two-step procedures. The first stage is called the prediction stage which is relying on the previous iteration. This stage estimates the real-time system state besides its uncertainty. The second stage is the update stage which is based on the observed measurement for the prediction stage and its uncertainty. By using a weighted average, the prediction step is refined and updated [12]. The Kalman filters-based methods being used in PSDSE can be summarized in three types: Kalman Filter (KF), Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). Firstly, the KF is used to model the dynamics of the linear system. Instead of depending on the measurements alone, the additional information provided by this method grants less computations which lead to a better estimate

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of the system state[12], [13]. Secondly, the EKF is suitable for the non-linear systems which are more appropriate for the power system. The EKF is used for estimation of the non-linear systems by linearizing system model functions and non-linear measurement function around an operating point. To linearize a system, the Jacobian calculation (using first-order Taylor series) has to be done [14]. The EKF algorithm in power system state estimation has proposed in different studies [15], [16], [17]. The last type of Kalman Filters is the UKF which is similar to EKF in its application. However, the UKF is more efficient than EKF, specifically when the nonlinearities of the system are increased in such an extensive system like power system; but it needs much more computational burden[15], [18].

In this paper, we proposed Smooth Variable Structure Filter (SVSF) for DSE in smart power grids. The SVSF was first proposed in 2007, which was applied to smooth nonlinear dynamic systems, and its formulation is a predictor-corrector mode. This method is robust to model errors and uncertainties, and it is able to detect system changes[18], [19]. The EKF and UKF are also implemented to examine the efficiency of the proposed SVSF approach.

This rest of the paper is organized as follows: Section II describes the proposed method SVSF and Section III defines the network model as the applied system and after that presents simulation procedures and Results are provided in Section IV. Finally, this paper is concluded in section V.

II. SMOOTH VARIABLE STRUCTURE FILTER

The SVSF is a revised version of the variable structure that was published in 2007, which applied to smooth non-linear dynamic systems [20]. The SVSF is constructed as a predictor-corrector based on variable structure and the system theory in which can be applied to linear and non-linear systems. This filter can greatly deal with uncertainties correlated with initial conditions and modeling errors[21], [22]. Additionally, the SVSF generally presumes that the applied system is differentiable and observable [23]. Moreover, SVSF is based on switching gain to converge the estimated state within a boundary of the true states and it has less complex computations compare to EKF and UKF[24]. Fig.1 Shows explain the flowchart of the SVSF estimation method. The SVSF algorithm has two stages: the prediction stage and the update stage which can be describe as follows:

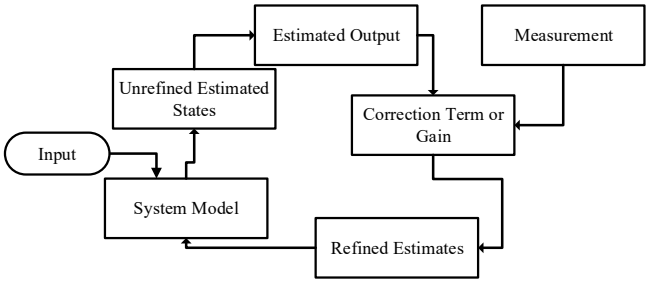

Fig. 1. The flowchart of the SVSF estimation method.

The SVSF algorithm is similar to the main concept of Kalman Filter. It has two stages: the prediction stage and the updated stage. The estimation's process is iterative and the following equations describe the SVSF procedure [20], by considering the non-linear system function in (1).

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, t_k) + w_k \\ y_k &= h(x_k, u_k, t_k) + v_k \\ w_k &\sim (0\,, Q_k) \\ v_k &\sim (0\,, R_k) \end{aligned} \tag{1}$$

1. The prediction stage:

$$\begin{aligned} \hat{x}_{k+1}^{pr} &= A\hat{x}_k^{pr} + Bu_k \\ P_{k+1}^{pr} &= AP_k^{pr}A^T + Q_k \\ e_{z,k+1}^{pr} &= Z_{k+1} - C\hat{x}_{k+1}^{pr} \end{aligned} \tag{2}$$

In equation (2), $\hat{x}_{k+1}^{pr}$ and P_{k+1}^{pr} are the predicted state estimates and state error covariances respectively. The A matrix should be obtained from the first-order Tylor series linearization of the non-linear function, which is called the process matrix. Additionally, the $e_{z,k+1}^{pr}$ equation is called the measurement innovation equation which has the measurement matrix Z_{k+1} and the $C\hat{x}_{k+1}^{pr}$ can be calculated by using the non-linear measurement function $h(.)$ [25].

2. The measurement updated stage:

$$K_{k+1} = \left[\frac{\left(H^{-1}diag(E\ sat)\right)}{\left(e_{z,k+1}^{pr}\right)}\right] \tag{3}$$

K_{k+1}in equation (3) is the gain which is used to calculate $\hat{x}_{k+1}^{pos}$ and P_{k+1}^{Pos}. Where H should be linearized from the non-linear measurement function $h(.)$ to be obtained, and E can be computed from (3). γ in (4) refers to Memory or convergence rate. Also, the sat can be calculated in (5) and φ is the smoothing boundary layer width (SBL) which is defined in (6), where m is the number of measurement [26].

$$E = \left|\left(e_{z,k+1}^{pr}\right)\right| + \gamma\left|e_{z,k}\right| \tag{4}$$

$$sat = \begin{cases} \sin\left(\frac{e_z}{\varphi}\right) & for\ \left|\frac{e_z}{\varphi}\right| \geq 1 \\ \frac{e_z}{\varphi} & else \end{cases} \tag{5}$$

$$\varphi = \begin{bmatrix} \varphi & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \varphi_m \end{bmatrix} \tag{6}$$

In the following equations (7,8,9) we can obtain the update of: the state estimate $\hat{x}_{k+1}^{pos}$, the state error covariance $P_{k+1}^{pos}$and the measurement innovation $e_{z,k+1}^{pos}$.

$$\hat{x}_{k+1}^{pos} = \hat{x}_{k+1}^{pr} + K_{k+1}\, e_{z,k+1}^{pr} \tag{7}$$

$$P_{k+1}^{pos} = \left[(I - K_{k+1}H)\, P_{k+1}^{pr}\, (I - K_{k+1}\, H)^T + (K_{k+1}R_{k+1}K_{k+1})\right] \tag{8}$$

$$e_{z,k+1}^{pos} = Z_{k+1} - h\left(\hat{x}_{k+1}^{pos}\right) \tag{9}$$

III. NETWORK MODEL

The power system of this paper is a Single-Machine-Infinite-Bus state space model [18], [27].The general power system model can be described as a single synchronous generator connected to a transformer and parallel transmission lines

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through infinite bus. This system is modeled as the fourth order state space model in dq0 reference frame as described in (10).

$$X = \left[\delta \ \Delta\omega \ \acute{e}_q \ \acute{e}_d\right]^T = [x_1 \ x_2 \ x_3 \ x_4]^T$$

$$U = \left[T_m \ E_{fd} \ V_t\right]^T = [u_1 \ u_2 \ u_3]^T$$

$$\dot{x}_1 = \omega_0 x_2$$

$$\dot{x}_2 = \frac{1}{J}\left[T_m - \left(\frac{V_t}{\dot{x}_d} x_3 \sin(x_1) + \frac{V_t^2}{2}\left(\frac{1}{x_q} - \frac{1}{\dot{x}_d}\right)\sin(2x_2)\right) - Dx_2\right] \quad (10)$$

$$\dot{x}_3 = \frac{1}{\dot{T}_{d0}}\left[E_{fd} - x_3 - (x_d - \dot{x}_d)\left(\frac{x_3 - V_t\cos(x_1)}{\dot{x}_d}\right)\right]$$

$$\dot{x}_4 = \frac{1}{\dot{T}_{q0}}\left[-x_4 + (x_q - \dot{x}_q)\left(\frac{V_t \sin(x_1)}{x_q}\right)\right]$$

$$y_1 = \left[\frac{V_t}{\dot{x}_d}(x_3)\sin(x_1) + \frac{V_t^2}{2}\left(\frac{1}{x_q} - \frac{1}{\dot{x}_d}\right)\sin(2x_1)\right]$$

Equation (10) presents the forth order state space model for the applied nonlinear synchronous machine. The definition of the main parameters in (10) as follows: $\acute{e}_q$ *and* $\acute{e}_d$ are the d-and q-axis voltages, $\Delta\omega$ is the rotor speed, δ is the rotor angle, T_m is the mechanical input torque, E_{fd} is steady state internal voltage of armature, V_t is the terminal bus voltage, x_d, x_q are the direct and quadratic axis reactance, $\dot{x}_d, \dot{x}_q$ are the direct and quadratic axis transient reactance, and D, J are the damping factor and inertia constant, which all the quantities are in per unit. Additionally, the direct and quadratic axis transient open circuit times constant in second are $\dot{T}_{d0}, \dot{T}_{q0}$ respectively. Along beside the parameters, the only output of this system is presented in y_1 which is non-linear equation. The state space model of this system is being discretized by using the first-order of Taylor Series. In this model, the presence of PMU provides a high rate date which makes the on-line state estimator observable. The definition of variables and constant with the machine test and external system data are provided in [18], [27].

IV. Simulation And Discussion

A. MATLAB Implementation

The simulation of the proposed method is performed embedded MATLAB function block, which creates a MATLAB code page in the Simulink model, and system model in parallel. The Simulink function block is used to make connection between the signals obtained from the single machine infinite bus model (A synchronous generator connected to an infinity bus) and the estimation algorithms (EKF, UKF and SVSF). We have run the simulation separately for each method of which the EKF and UKF were implemented in order to compare them with the proposed SVSF method. In the Simulink, we basically replaced the embedded SVSF block in Fig. 2 by the equivalent block of EKF and UKF.

In all estimators T_m, E_{fd}, and V_t are considered as their input signals. For the sake of step response simulation studies (system dynamics study), a step function (with initial value=0 and final value= 0.2) was added to the constant value of E_{fd} (provided in Table I) at the time 1 sec and mechanical torque input T_m was fixed at 0.8.

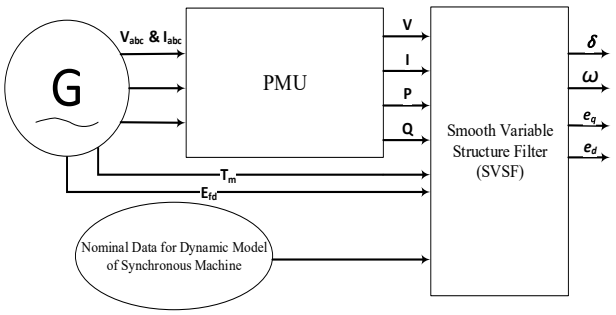

Fig. 2. Implementation of SVSF estimator using embedded MATLAB function block.

B. Results and Discussion

All of the estimation approaches used in this paper were implemented in two conditions which are normal and presence of measurement outliers.

1) Normal Condition:

In the Normal case, a noise added to the system dynamics model while the step input was added to the steady state internal armature voltage. In order to characterize a near real system condition for the EKF, UKF and SVSF estimators, Gaussian white noise was applied to the process states and measurable output as well. The mean and covariance of the noise added to the system and measurement are $(0, 0.001^2 \times (I_{4\times4})$ and $(0, 0.1^2 \times I)$, respectively. The result of the state estimation error in the noisy environment is presented in Fig. 3 (a) and Fig. 3 (b) for the estimated states and the estimated output, respectively. As can be seen, in the normal condition both SVSF and UKF estimator could well track the dynamics of the system based on excitation voltage step response.

Root Mean Squared Error (RMSE) results for all the three estimators in normal condition are also given in Table I. According to the data provided in Table I, in the noise condition, for all filters the error between the actual and estimated signal is small enough.

TABLE I. RMSE OF ESTIMATED STATES AND OUTPUT FOR NOISY CASE

Filter		EKF	UKF	SVSF
States	δ (pu)	0.030828	0.018651	0.031236
	$\Delta\omega$ (pu)	0.0012439	0.0025768	0.00099936
	e'_q (pu)	0.037196	0.024397	0.037299
	e'_d (pu)	0.010452	0.00733	0.010647
Output	P_t (pu)	0.028099	0.018651	0.031236

Although this amount of error is acceptable, it would be higher when some measurement outliers applied to the system. The effect of outliers on the estimators' accuracy is investigated in the next section.

2) Presence of Measurement Outliers Condition:

In this case, the same noise presented in normal case was applied to the system model. For each estimator, four consecutive measurement outliers are applied to the system starting from 1 second and happened every 4 seconds (at: 1, 5, 9 and 13 seconds). The amplitude of outliers is considered to be 1.5 times the original measurement. These measurement outliers in the real world can be occurred as a result of bad sensor data or false data injection (FDI) attack to the measurement data.

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To compare the performance of different estimators under outliers' condition, EKF, UKF and SVSF methods were separately implemented to estimate the system dynamic states and output. As observed by comparing errors between estimated and true values for all three filters depicted in Fig. 5, SVSF algorithms significantly perform more accurately and smoothly than the EKF and UKF approaches in outliers' conditions. In fact, EKF and UKF estimation results are more biased (like for rotor angle and transient voltages) while SVSF estimates does not have this noticeable deviation from the true states and generate very accurate states after all the applied measurement outliers. However, the SVSF have wrong estimates for a couple of milliseconds and then it could track the states very well whereas the EKF and UKF have unacceptable state estimation results, such as those for the rotor angle and transient voltages estimates.

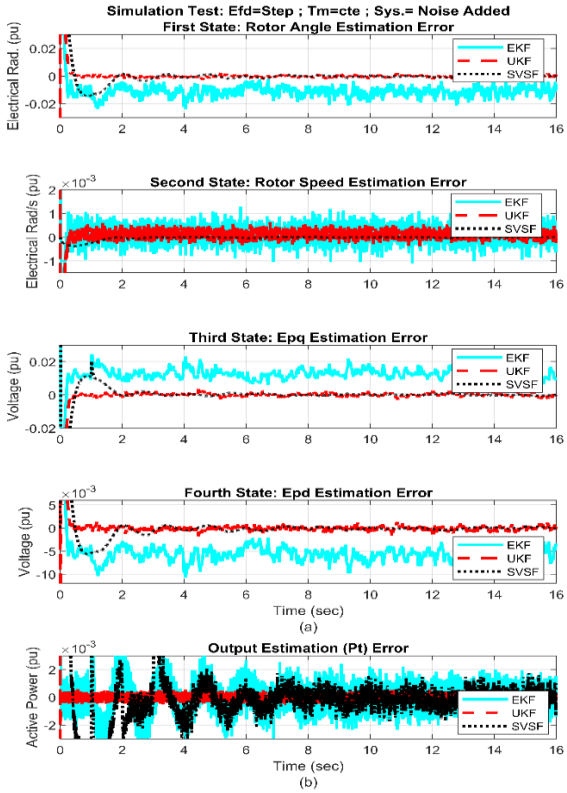

Fig. 3. Estimation error of three implemented estimators' results for normal condition: (a) States error. (b) Output error.

For more detailed analysis, root mean squared error (RMSE) results for all the three estimators in the presence of measurement outliers are provided in Table II. which approves that the SVSF has the most accurate estimated results.

TABLE II. RMSE OF ESTIMATED STATES AND OUTPUT FOR MEASUREMENT OUTLIERS

Filter		EKF	UKF	SVSF
States	δ (pu)	26.095	3.6808	0.039458
	$\Delta\omega$ (pu)	0.0099071	0.025539	0.0010068
	e'_q (pu)	0.75032	0.60222	0.044151
	e'_d (pu)	0.13557	0.36957	0.013931
Output	P_t (pu)	0.037329	0.6808	0.039458

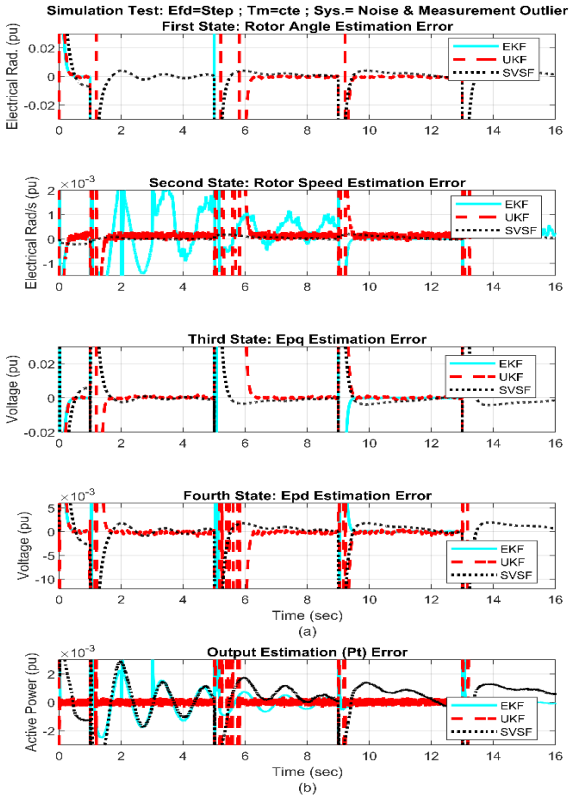

Fig. 4. Estimation error of three implemented estimators results in presence of the measuerment outliers: (a) States error. (b) Measurable output error.

V. CNONCLUSION

In this paper, the SVSF-based dynamic state estimation approach was applied to a single synchronous generator connected to the infinite bus. The proposed method was compared with EKF and UKF results to validate the SVSF estimation result. Two scenarios were considered in the simulation procedure: normal condition and the presence of measurement outliers one. The normal case results show that SVSF and UKF filters have more accurate estimation results and all three filters have an appropriate RMSE results.

In the second scenario, the state estimation results present that the SVSF works efficiently and accurately in presence of the measurement outliers with the highest level of tracking smoothness compared to the EKF and UKF, prominently in rotor angle and transient voltages estimations. However, studying these filters specifically UKF and SVSF under different faulty conditions of the power system seems to be necessary as the future work.

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