A Method for Extracting Steady State Components from Syncrophasor Data using Kalman Filters

Farhan Mahmood
KTH Royal Institute of Technology
Stockholm, Sweden
Email: farhanm@kth.se

Hossein Hooshyar
KTH Royal Institute of Technology
Stockholm, Sweden
Email: hossein.hooshyar@ee.kth.se

Luigi Vanfretti
KTH Royal Institute of Technology Stockholm
Statnett SF, Oslo, Norway
Email: luigiv@kth.se, luigi.vanfretti@statnett.no

***Abstract*—Data from Phasor Measurement Units (PMUs) may be exploited to provide steady state information to the applications which require it. Raw PMU data is polluted with noise and cannot be directly fed to applications without adequate processing. This paper presents a method to extract steady state components from Syncrophasor data using Kalman Filters (KF). This method is capable of reducing the noise, to compensate for missing data and filtering of outliers in signals. The Residue in each KF iteration is computed. The measurement noise covariance matrix R is calculated by computing the variance of residue using rolling windows. The performance of presented method is evaluated by using PMU data generated from a Hardware-In-the-Loop (HIL) experimental setup.**

***Index Terms*—Data processing, Kalman filters, Phasor measurement units, Real-Time Simulation**

I. Introduction

A. Motivation

Funded by the European Commissions FP7 program (7th Framework Programme for Research and Technological Development), the IDE4L (Ideal Grid for All) project has started to define, develop and demonstrate a distribution network automation system, IT systems and applications for active network management [1]. The project is composed of several work packages to cover different aspects of active network management. As part of work package 6 of the project, intelligent applications for monitoring, control and protection of the grid are being developed by exploiting PMU data. As required by IEEE standard [2] the total vector error (TVE) between a measured phasor and its reference value should be less than 1% under steady state operation. However, in field installations, this criterion is not met due to the presence of different measurement uncertainties in PMU data [3]. Bad PMU data can distort Wide Area Monitoring System (WAMS) displays, jam calculation engines, or cause improper alarming [4]. Therefore there is a clear need to process PMU data before using it in different applications. In [4][5][6] some methods of correcting different types of errors in PMU measurement are presented.

B. Previous Work

Measurements obtained from PMUs during different events in power systems contain different signal features at different time scales. Hence they contain features of different types of power system dynamics. In addition, not all PMU applications need the same type of signal. In order to feed this data to different applications effectively, it should be processed in different ways before feeding it to applications. For steady state applications, like conventional state estimation, the presence of oscillations and noise around the steady state will impact the performance of the application. Therefore there is a need to remove these dynamic components from signals to effectively use them in steady state applications. In [7], a method of extracting the steady state is presented using FIR and Median filters. Noises, outliers and missing data in PMU measurements are ignored in this filtering method. In [7], the method has been discussed only for offline applications.

C. Paper Contributions

Previous works do not consider that different applications will only utilize information about an specific time-scale contained in PMU data. The novelty of this paper is to apply a Kalman Filter method to separate the different time-scales. The method has been developed in such a way that it can be used in near real time applications. The added value of such approach is to provide the "right" kind of information contained in the PMU data for the time-scale at which steady state applications (such as contingency analysis) or others operate. In addition, the method is also capable of filtering noise, compensating for missing data and removing the outliers in PMU signals. In order to apply and interpret the results of the proposed method, signal features corresponding to power system dynamics are removed by updating the value of R, (using results from) [8]. In the method proposed here, residue is calculated in each iteration of the KF. R is calculated by computing the variance of computed residue. The value of R is updated accordingly for the next correction step

The remainder of the paper is organized as follows: In Section II, a general approach for PMU data processing is presented. Section III describes the KF method implemented in this paper in detail. Different case studies and results are presented in Section IV. Finally, Section V presents the key conclusions drawn from the results in this paper.

II. Approach for Generalized PMU Data Processing for Distribution Network Applications

A. Data Processing Overview

Fig. 1 shows a PMU signal containing some typical events in the power system bearing dynamics at different time

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scales. Typical power system dynamic phenomenon that can be identified from different components of PMU signals are:

- Discrete Events (e.g. transmission line switching) (Transient stability) $\sim$ Milliseconds
- Small signal stability $\sim$ Seconds
- Tap changer operation (Voltage stability) $\sim$ Minutes

Identifying these events enable the system operator to take appropriate actions in time. Depending upon the nature of these events, actions can be preventive, corrective or restorative [9]. Therefore it is very important that the PMU applications which are used to identify the type of dynamic process are provided with "clean" data so that no false actions can be taken based on the results. The power system's response to these events within the PMU data, require that the PMU data is processed in different ways in order to feed the resulting processed signal to specific PMU applications e.g. state estimation. The processing of PMU data can also be application specific, i.e. in order to feed the signal shown in Fig. 1 to steady state and dynamic applications, the processing should be different in both cases. The focus of this paper is steady state applications, so the raw PMU data is processed in an appropriate way in order to extract the steady state component from the signal.

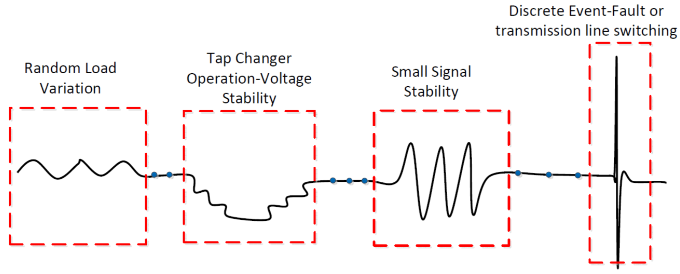

Fig. 1. Signal features at different time scales in a PMU signal

B. Problems in PMU Measurements

Fig. 2 shows a voltage magnitude as generated by a PMU using a Hardware-In-the-Loop (HIL) lab setup. Discrete events, such as, tap changer operation results in outliers in PMU data, as can be seen on the left hand side of Fig. 2. These outliers can affect the performance of target applications. The other problem shown in Fig. 2, is the missing data. Missing data is not acceptable for many applications as calculations may be affected. Also shown in Fig. 2 is the problem of measurement noise. Feeding noisy data to steady state applications can lead to wrong results.

Therefore, all of these practical problems need to be addressed by using appropriate data processing methods. A data processing method using KF is adopted in this paper to overcome these issues, as discussed next.

III. Implementation Method

This section presents first the theoretical background of traditional KF. For details the readers are refered to [10] [11].

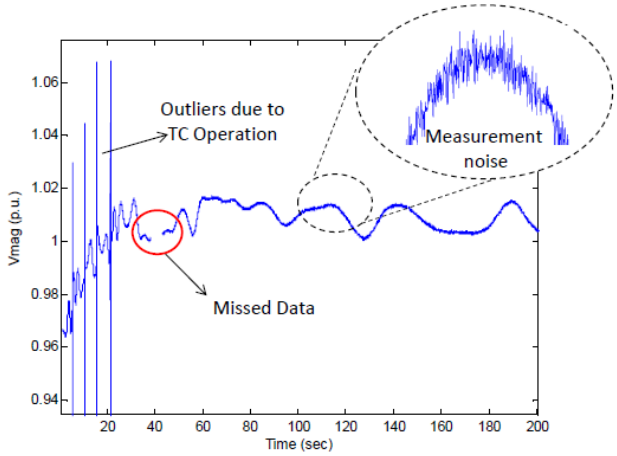

Fig. 2. Problems in PMU Voltage Measurement

Second, our contribution on the application of the KF method is described. In the last subsection, the experimental setup to generate PMU data used in section IV is explained.

A. The Kalman Filter (KF)

A linear discrete time controlled process is assumed to have linear stochastic process equations and measurement equations

$$\begin{aligned} x_k &= Ax_{k-1} + Bu_k + w_{k-1} \\ z_k &= Hx_k + v_k \end{aligned} \tag{1}$$

where x is the state vector, z is the measurement vector, A is the $n \times n$ matrix that relates the state at previous time step $k-1$ to the state at current step k, which is assumed to be constant in each iteration, B is the control input which relates input u to the state x and H is the $m \times n$ matrix which relates state x_k to the measurements z_k. The process noise w_k and measurement noise v_k are assumed to be two mutually independent random variables with normal probably distributions

$$\begin{aligned} p(w) &\sim \mathcal{N}(0, Q) \\ p(v) &\sim \mathcal{N}(0, R) \end{aligned} \tag{2}$$

where Q is process noise covariance matrix and R is measurement noise covariance matrix, these two matrices are usually constant but can be updated at each time step.

The a priori state estimate $\hat{x_k}^-$ is defined as the estimate at step k, given knowledge of the process prior to step k. An a posteriori state estimate $\hat{x_k}$ is the estimate at time step k given the measurement z_k. In this respect the priori estimate error and a priori estimate covariance are given respectively as $e_k^- \equiv x_k - \hat{x_k}^-$ and $P_k^- \equiv E[e_k^- e_k^{-T}]$. Similarly, the a posteriori estimate error and a posteriori estimate covariance are given respectively as $e_k \equiv x_k - \hat{x_k}$ and $P_k \equiv E[e_k e_k^T]$.

The KF estimates the state by using feedback control: the filter estimates the process state at some time and then obtains feedback in the form of noisy measurements. KF can be divided into two parts:

Time update equations (Prediction): The time update equations are responsible of projecting forward (in time) the previous state $\hat{x}_{k-1}$ and error covariance estimate P_{k-1} to obtain the a priori estimates for the next step k. The time update equations are considered to be the predictor equations.

$$
\begin{aligned}
\hat{x_k}^{-} &= A\hat{x}_{k-1} + Bu_{k-1} \\
P_k^{-} &= AP_{k-1}A^T + Q
\end{aligned}
\tag{3}
$$

Measurement update equations (Correction): Measurement update equations are responsible for feedback by incorporating a new measurement z_k into the a priori estimate to obtain an improved a posteriori estimate. The measurement update equations can be thought of as corrector equations.

$$
\begin{aligned}
K_k &= P_k^{-} H^T (HP_k^{-}H^T + R)^{-1} \\
\hat{x_k} &= \hat{x_k}^{-} + K_k(z_k - H\hat{x_k}^{-}) \\
P_k &= (I - K_k H)P_k^{-}
\end{aligned}
\tag{4}
$$

where K is an $n \times m$ matrix known as Kalman gain matrix, z_k is the actual measurement at step k, $H\hat{x_k}^{-}$ is the predicted measurement, $\hat{x_k}$ is the a posteriori estimate which is a linear combination of an a priori estimate $\hat{x_k^{-}}$ and a weighted difference between an actual measurement and predicted measurement. From the above expressions it can be concluded that as R approaches zero, an actual measurement z_k is trusted more and predicted measurement $H\hat{x_k}^{-}$ is trusted less. On the other hand, as the a priori estimate error covariance P_k^{-} approaches zero, the predicted measurement is trusted more than the actual measurement.

To summarize, the KF is a predictor-corrector algorithm. After each time and measurement update pair, the process is repeated with the previous a posteriori estimates used to project a new priori estimate. In addition, the KF does not require all the previous data at each estimate, instead, it just recursively conditions the current estimate on all the past measurements. This makes the KF a suitable method for real time applications.

B. Kalman Filter Application and Implementation

KF is implemented in this paper to extract the steady state components from PMU signals. This is carried out by assuming that dynamic components in the PMU data are measurement noise. According to [8], accuracy of state estimators using KF are largely influenced by measurement and process noise covariance matrices, i.e. R and Q. Therefore, KF is applied to reduce the noise and increase the accuracy of PMU data by updating the value of R in each KF iteration. The KF algorithm was implemented in MATLAB. PMUs have 4 state variables to be estimated, i.e. V, θ, I, δ, which corresponds to the variables that a PMU measures [6]. Assumed process model given in (1), A is an identity matrix because the time step between KF iterations are small enough to assume that the current state is equal to the previous state[1], B is zero as there is no input to the process and H is also an identity matrix because the states are directly measured.

[1]This assumption is valid for PMU reporting rates of above 30 samples per seconds.

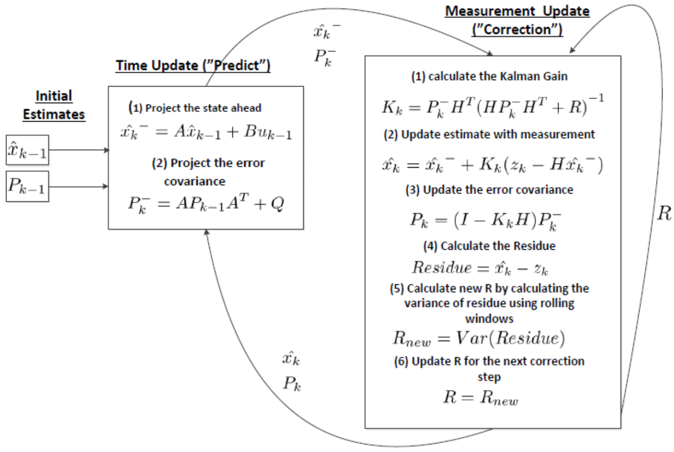

Fig. 3. Kalman Filter Overview

The overview of the KF implementation is shown in Fig. 3. The initial estimate of $\hat{x}_{k-1}$ and $\hat{P}_{k-1}$ are the input to the time update (prediction step). The predictor step is the same as given in equation (3), projecting forward (in time) the previous state and error covariance estimate to produce the state and error covariance for the next step. The corrector step is, however, not the same as used in conventional KF. Instead, in addition to equation (4), a Residue is calculated as the difference between state estimation $\hat{x}_k$ and actual measurement z_k

$$
Residue = \hat{x_k} - z_k \tag{5}
$$

The variance of the calculated residue in equation (5) is computed in each step in equation (6) using rolling windows .This gives the measurement covariance matrix R.

$$
\begin{aligned}
R_{new} &= Var(Residue) \\
R_{new} &= E[(Residue - E[Residue])^2]
\end{aligned}
\tag{6}
$$

where E represents the mathematical expectation of the value. R is therefore updated in each time step, and is used in the start of next correction step.

$$
R = R_{new} \tag{7}
$$

It was observed that instead of using a whole parcel of data at a time, using rolling windows in time gives better results. For example, small signal oscillations and noise in the PMU data can be effectively filtered out by updating the value of R in rolling windows. During the period when oscillations are large, a large difference between actual measurement z_k and state estimation x_k occurred, causing the residue to be higher. As R is calculated on the basis of the residue, R becomes larger as well. In this case the actual measurement z_k is trusted less, while a priori state estimation $\hat{x_k^{-}}$ is trusted more when calculating the new estimate $\hat{x_k}$. Therefore oscillations can be easily filtered out and a smoother response is obtained for steady state applications. The size of rolling window is also an important factor which will be discussed in section IV-C

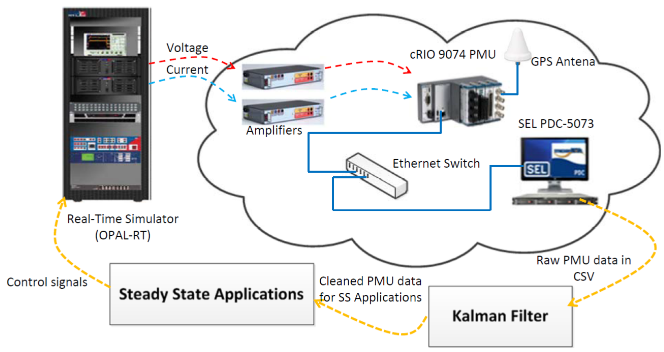

Fig. 4. Hardware in the loop (HIL) Lab Setup

C. Experimental setup for generating PMU data

The PMU data is generated using a Hardware-In-the-Loop (HIL) lab setup as shown in Fig. 4. A SimPowerSystems (SPS) model is simulated in real time (hardware synchronized mode) using an OPAL-RT simulator [12]. The voltage and current are available at the analog output channel of the simulator. These quantities are acquired by a National Instrument Compact Rio (NI cRIO) 9074 PMU[13], with software configured to perform PMU functions [14] through voltage and current amplifiers by Megger [15]. The network connection of the PMU streams the data to a Phasor Data Concentrator (PDC) server. The raw PMU data was acquired from the PDC and archived in Comma Separated Values (CSV) format to be fed to the KF execution environment.

IV. Case Studies and Results

A. Difference between simulated data and PMU data

WAMS application development cannot rely on simulated data. There are many practical issues which can be observed from real PMUs which are not present in simulations. For example, Fig. 5 shows a very clear illustration for this argument. A power system is disturbed with random load variations (RLV) $t = 45sec$ and deactivated at $t = 115sec$. The voltage response from the simulation and the HIL PMU setup is shown in Fig. 5. It can be clearly seen that the voltage from the HIL PMU setup has missing data, which is due to the fact that the PMU data is delayed for a longer time than the PDC maximum waiting time. Also with the discrete event of connection and disconnection of the RLV, PMU generates outliers. Hence, in the development of the method in section III-B and the example below, only data from the RT HIL setup is used.

B. Kalman Filter Performance

The developed KF method is applied on HIL PMU data. The disturbance here is the same as in Section IV-A. The results for the PMU voltage magnitude and PMU voltage angle are shown. The top of Fig. 6 shows the KF algorithm performance for the PMU voltage magnitude signal. It can be seen that missing data is compensated for (can be seen in zoomed in view). As soon as the KF detects a missing data point, it holds the value of the previous state. When the disturbance is applied at $t = 45sec$ and removed at $t = 115sec$, outliers are generated in the PMU voltage signal. The RLV excites the small signal oscillations, which should be neglected in a steady state application. Hence by updating the R as explained in Section III-B, the dynamics and outliers are filtered, giving a much smoother response for use in steady state applications. The resulting response of R is shown in the bottom of Fig. 6.

The top of Fig. 7 shows the KF algorithm performance for the PMU voltage angle signal. Similar to the voltage magnitude, the KF compensates for missing data (can be seen in zoomed in view). The RLV also excites the small signal oscillations in PMU voltage angle signal. These dynamic components are removed by updating the value of R, in each iteration in the correction step of KF algorithm (response of R shown in bottom of Fig. 7). Hence smoother estimation for the voltage angle is obtained as shown in red in the top of Fig. 7.

C. Impact of varying rolling window length on smoothing

As mentioned in Section III-B, the size of the Rolling Window (RW) affects the smoothing of the states in the presence of outliers and oscillations. By varying the RW length, the updating of R varies, resulting in different responses for signal smoothing. Fig. 8 shows different responses for the PMU voltage magnitude with different lengths of RW. For length of RW= 0.5 seconds, a fast KF response is obtained together with a smoothed output which captures the exponential decay of the small signal oscillations. However, as soon as the RW length increases, the response of the KF becomes slower. For example the response for RW= 5 seconds (middle part of Fig. 8, zoomed in view of top part) is slow and it could not produce accurate smoothing. It can be thought of an over filtered response. The bottom of Fig. 8 shows different responses when updating R with variable RW length.

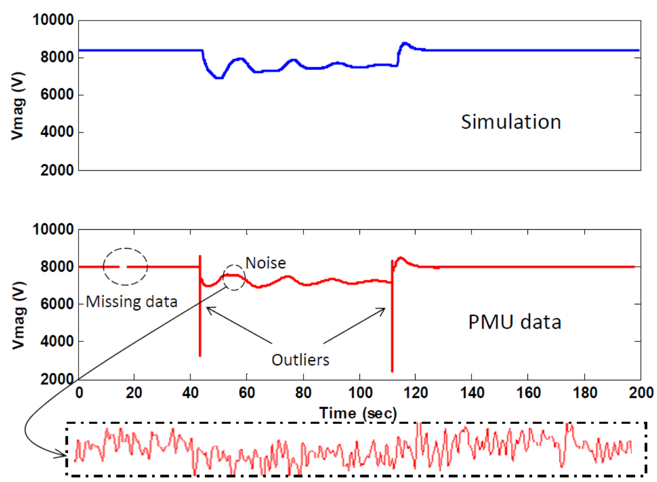

Fig. 5. Difference between voltage responses from simulation and an actual PMU for the same disturbance

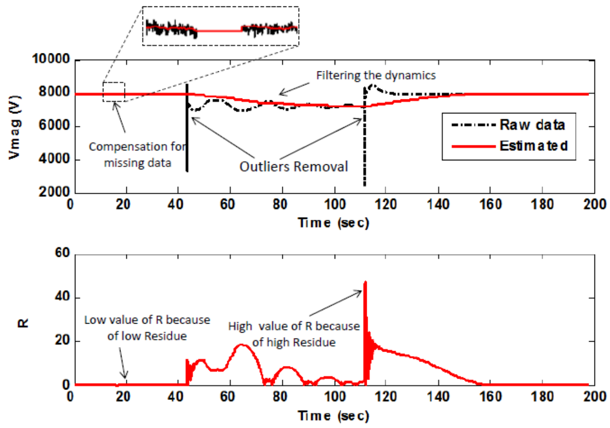

Fig. 6. Kalman Filter output for the PMU's voltage magnitude signal

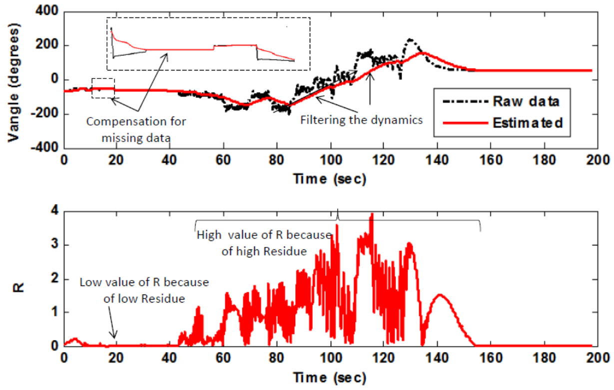

Fig. 7. Kalman Filter output for the PMU's voltage angle signal

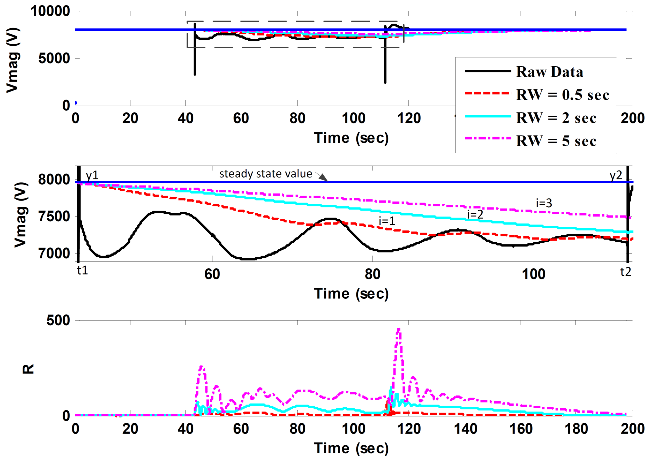

Fig. 8. Impact of variation in rolling window size on smoothing

D. Performance Analysis

Table I shows the performance analysis of the KF algorithm for different RW lengths. The value of standard deviation (SD) is minimum for RW = 0.5 sec, which means that certainty is maximum for this case. Secondly, the areas between the steady state value and the filtered signals are calculated using (8):

$$A_i = \int_{t1}^{t2} f_0(t)dt - \int_{t1}^{t2} f_i(t)dt \tag{8}$$

where f_0 is a straight line at (t_1, y_1) and (t_2, y_2) and $i = 1$, 2 and 3 correspond to the filtered signals with RW lengths of 0.5, 2 and 5 sec, respectively (see Fig. 8). The integral is computed in MATLAB using the trapezoidal numerical integration `trapz` command.

The evaluation metric A/K, i.e. per united area, has the highest value for the case RW = 0.5 sec. Here, K is the base value for calculating per unit area. Table II shows the computational time for different RW lengths. As the calculated results varied stochastically, the computations were repeated 50 times to obtain averaged values, as shown in Table II. It is evident that RW = 0.5 sec has lowest computational effort.

Hence, the performance analysis of this KF algorithm shows that a faster response is obtained with a small RW length and more adequate signals to be used in steady state applications are produced. This is because a small RW length gives better smoothing with less computational effort.

TABLE I
KF PERFORMANCE METRICS FOR DIFFERENT RWS

$RW(sec)$	R_{min}	R_{max}	R_m	$SD(\sigma)$	$Area$	A/K
0.5	0.027	72.9	6.83	8.31	1401973	0.88
2	0.023	146	35.6	21.07	1168762	0.77
5	0.0152	456	106.81	68.50	810802	0.54

TABLE II
AVERAGE COMPUTATIONAL EFFORT FOR DIFFERENT RWS

$RW(sec)$	$CompTime(sec)$
0.5	4.3272
2	4.3543
5	4.4320

V. CONCLUSIONS AND FUTURE WORK

The results in this paper show that the proposed method using Kalman Fitlers is suitable for processing PMU data to be fed to steady state applications. It has been shown that by updating the value of measurement noise covariance matrix R, appropriately, dynamics can be filtered out from PMU data to obtain a smoother response to be used in steady state applications. The proposed KF method has been developed for real time implementation, as it does not require all previous data points to predict the next state, instead it recursively conditions the current state on all the past measurements. Currently, the authors are working on a real time implementation of this method using LABVIEW, results from this work will be presented in our future publications.

Acknowledgments

This work was supported in part by EU-funded FP7 IDE4L Project, the STandUP for Energy Collaboration Initiative and by Statnett SF, the Norwegian Transmission System Operator.

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