Electric Power System Static State Estimation through Kalman Filtering and Load Forecasting

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***Abstract*—Static state estimation in electric power systems is normally accomplished without the use of time-history data or prediction. This paper presents preliminary work on the use of the discrete-time Kalman filter to incorporate time history and power demand prediction into state estimators. The problem of state estimation combined with the knowledge of the forecasted load is posed as a Kalman filtering problem using a novel discrete-time model. The model relates current and previous states using the electric power flow equations. An IEEE 14-bus test system example is used to illustrate the potential for enhanced performance of such Kalman filter-based state estimation.**

***Index Terms*—Kalman filtering, power system, power system state estimation, power transmission, state estimation.**

I. Introduction

STATE estimation is the process of determining a best estimate for the present state of a given system through the processing and interpretation of measurements from the sensors monitoring the system. In the case of a power system, the state is the vector of phasor voltages at all the busses. The phasor angles and magnitudes are estimated as separate state variables. For a network with N busses, the state is

$$\mathbf{x} = [\delta_1 \quad \delta_2 \quad \dots \quad \delta_N \quad V_1 \quad V_2 \quad \dots \quad V_N]^T \tag{1}$$

If sufficiently accurate synchronized measurements of the voltages were available, the state could be inferred directly. This method, however, is highly susceptible to measurement error and these measurements are generally not available with sufficient accuracy to provide an effective estimate of the state [1]. Instead, the state is estimated from measurements of voltage magnitudes (V_i), branch current magnitudes (I_{ij}), real and reactive branch power flows (P_{ij} and Q_{ij}), and real and reactive node power injections (P_i and Q_i).

Schweppe describes in [2] how these measurements are typically taken as a snapshot, or scan, of the network and used to find the static state of the system at that time. A weighted least-squares method is typically employed to estimate the state that best fits the measurements, where the best fit is a set of state values that minimizes the weighted sum of the square of the residuals.

Methods utilizing discrete time dynamic estimation have been proposed [3-6]. These methods use various dynamic models that do not explicitly account for the power flow constraints and also do not use the load forecast to predict the state transition. Other methods [11-12] implement state prediction, where a dynamic model is generated through online identification using linear exponential smoothing and load forecasting. The inclusion of dynamic models provides the basis for performing the state estimation via Kalman filtering [7].

This paper builds on previous work in [8] that explored the use of a power flow-based dynamic model driven by load forecasts and estimated the state using an extended Kalman filter (EKF). This technique was demonstrated on a simulated 4-bus system and estimated the phasor angle portion of the state vector using real power measurements only. This paper expands the scope of [8] by exploring estimation of the full state vector with both real and reactive power measurements. The iterated Kalman filter (IKF) [9,12] is used to provide improved accuracy over the EKF. The IEEE 14-bus test system (Fig. 1) is used in [5-6,11] to compare the performance of the proposed method to static state estimation.

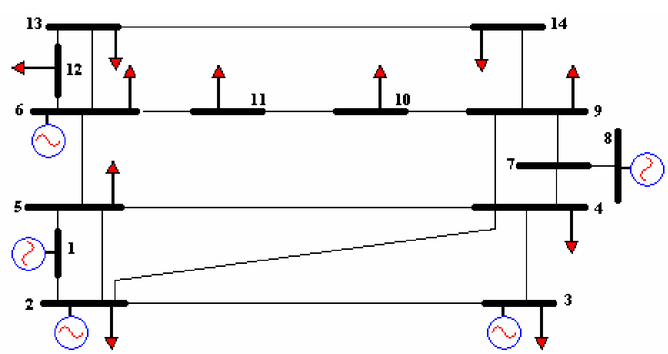

Fig. 1 IEEE 14 Bus Test System

II. Static State Estimation

The state of a static system can be described as a set of information that allows you to uniquely determine any variable of the system given an accurate model of how those variables are related to the state. These variables, which may

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include part of the state, may be measurable where the state as a whole may not be. As measurements are seldom exact, state estimation generally employs probabilistic methods to take into account the inaccuracies of the measurements to minimize the expected estimation error.

A. Measurement Model

Each measurement z_i, is uniquely calculated by a nonlinear function of the state $h_i(x)$ in the ideal case. Since measurements are not perfect, the measurements that the state estimator will process are assumed to be corrupted by zero-mean Gaussian noise, v_i=N(μ=0,σi), so that

$$\mathbf{z} = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_M \end{bmatrix} = \begin{bmatrix} h_1(x) \\ h_2(x) \\ \vdots \\ h_M(x) \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_M \end{bmatrix}. \quad (2)$$

The corresponding measurement Jacobian is represented as

$$\mathbf{H} = \frac{\partial \mathbf{h}(\mathbf{x})}{\partial \mathbf{x}^T}. \quad (3)$$

The noise on each of the measurements is typically assumed to be uncorrelated so that the covariance matrix,

$$\mathbf{R} = E\left[\mathbf{v}\mathbf{v}^T\right] = diag\left(\sigma_i^2\right) \quad (4)$$

is diagonal, where E[.] is the expectation operator. The magnitudes of the variances are based on the physical characteristics of the respective measurement devices such as their tolerances, measurement drift, etc.

For a power system, the state is generally defined as (1) while the measurement vector is:

$$\mathbf{z}_{static} = \begin{bmatrix} \mathbf{P}_I^{\ T} & \mathbf{Q}_I^{\ T} & \mathbf{P}_F^{\ T} & \mathbf{Q}_F^{\ T} & \mathbf{V}^T \end{bmatrix}^T, \quad (5)$$

where the subscript I indicates injection at a bus and the subscript F indicates flow between busses.

B. Estimating the state

When the measurement function is linear, i.e., **h(x)=Hx**, the state estimate may be directly determined through a weighted least squares estimate

$$\mathbf{x} = \left(\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{R}^{-1}\mathbf{z}_{static}. \quad (6)$$

For power systems, the function, **h(x),** by which the measurements are calculated from the state is nonlinear**.** Therefore, **x** cannot generally be calculated accurately in a single step as in (6). The state is therefore estimated by iteratively correcting the estimate from the measurement residuals. The correction at each iteration, k, is

$$\mathbf{x}^{k+1} = \mathbf{x}^k + \left(\mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{R}^{-1}\left(\mathbf{z}_{static} - \mathbf{h}\left(\mathbf{x}^k\right)\right), \quad (7)$$

where the iteration is initialized by setting x^k to the state estimate at the previous time step. The update is repeated until the stopping criterion is met. The stopping criterion is generally specified to be when the change in state between iterations falls below a pre-specified tolerance:

$$\left\| \hat{\mathbf{x}}^{k+1}[t+1] - \hat{\mathbf{x}}^k[t+1] \right\|_\infty \leq \varepsilon \quad (8)$$

A maximum number if iterations, K, may also be specified.

C. Augmenting the measurements with Load Forecast Data

This paper proposes two methods by which the accuracy of the state estimation result may be improved through the use of load forecasts. The first of these two methods involves inserting the load forecast directly into the measurement vector (17), giving the measurement vector

$$\mathbf{z}_{static+} = \begin{bmatrix} \mathbf{z}^T{}_{static} & \overline{\mathbf{P}}_i^{\ T} & \overline{\mathbf{Q}}_i^{\ T} \end{bmatrix}^T. \quad (9)$$

where $\overline{\mathbf{P}}_i^{\ T}$ and $\overline{\mathbf{Q}}_i^{\ T}$ are the vectors of forecasted real and reactive power injections. All load forecasts include some degree of uncertainty. The **R** matrix is extended with additional diagonal terms to account for this uncertainty. Similar to the basic static state estimation method, in this method the state estimate is calculated using the iterative procedure in (7) using $\mathbf{z}_{static+}$ instead of $\mathbf{z}_{static}$.

III. Dynamic State Estimation

Dynamic systems are governed not only by the state, but also by the dynamics of how that state changes due to an applied input. Knowledge of the dynamic state at a given time and the input to the dynamic system from that time forward allows the variables of the system at any future time to be uniquely determined.

Given a linear dynamical system with input and measurements corrupted with zero-mean Gaussian noise with known variance, the Kalman filter offers a recursive procedure to calculate the optimal state estimate. This is accomplished by updating the covariance of the state estimation error to account for new information received in both the prediction (based on the input) and the correction (based on the measurements) steps.

Implementation of the Kalman Filter requires a dynamic model that governs the transition between states and a measurement model that governs how the measurements are derived from the state.

A. Discrete-time Model Driven by Stochastic Changes in Demand

State estimation of electric power systems is the estimation of the static state. By definition, the static state has no memory of the static state at the previous time step. In other words, the state at the present time can be determined exactly from the network inputs at the current time regardless of the previous state value. Because the state can be determined from the input, if the input at two times is known, the state at those two times can be determined and thus the change in the state can be determined. The determination of change of a state as time progresses is the foundation of the dynamic model proposed here.

The balance between the input (real and reactive power at all the nodes) and the state is defined by the power flow equations. The power flow equation for node i is,

$$f_i(\mathbf{x},\Gamma) = V_i e^{j\delta_i} \sum_{k=1}^{N} \left(V_j e^{j\delta_j} \right)^* - \left(P_i + jQ_i \right) \quad (10)$$

where

$$\Gamma = \begin{bmatrix} P_1 & P_2 & \dots & P_N & Q_1 & Q_2 & \dots & Q_N \end{bmatrix}^T . \quad (11)$$

In any interconnected electric power grid, $f_i(\mathbf{x},\Gamma) = 0$.

Let

$$\mathbf{f}(\mathbf{x},\Gamma) = \begin{bmatrix} f_1(\mathbf{x},\Gamma) \\ f_2(\mathbf{x},\Gamma) \\ \vdots \\ f_N(\mathbf{x},\Gamma) \end{bmatrix}.$$

The full derivative **f**(**x**,**Γ**) reveals the following relation,

$$\frac{\partial \mathbf{f}(\mathbf{x},\Gamma)}{\partial \mathbf{x}} d\mathbf{x} + \frac{\partial \mathbf{f}(\mathbf{x},\Gamma)}{\partial \Gamma} d\Gamma = 0,$$

which leads to,

$$\mathbf{J} d\mathbf{x} = -\mathbf{I} d\Gamma \quad (12)$$

where

$$\mathbf{J} = \frac{\partial \mathbf{f}(\mathbf{x},\Gamma)}{\partial \mathbf{x}}, \quad (13)$$

and

$$\mathbf{I} = \frac{\partial \mathbf{f}(\mathbf{x},\Gamma)}{\partial \Gamma},$$

where **I** is the 2N by 2N identity matrix. Rearranging (12) to solve for d**x**, we have

$$d\mathbf{x} = -\mathbf{J}^{-1} d\Gamma . \quad (14)$$

We use this relationship to derive an expression for the difference in the state between two static operating points. The first operating point satisfies (10) as $\mathbf{f}(\mathbf{x}_1,\Gamma_1) = 0$ while the second operating point satisfies (10) as $\mathbf{f}(\mathbf{x}_2,\Gamma_2) = 0$. If the difference between the two operating points is infinitesimally small, we can apply (14) directly so that

$$\left(\mathbf{x}_1 - \mathbf{x}_2 \right) = -\mathbf{J}^{-1} \left(\Gamma_1 - \Gamma_2 \right).$$

If the difference is not infinitesimal, a new term $\mathbf{w}_{\underline{le}}$ representing the linearization error between the two operating points is introduced, resulting in

$$\left(\mathbf{x}_1 - \mathbf{x}_2 \right) = -\mathbf{J}^{-1} \left(\Gamma_1 - \Gamma_2 + \mathbf{w}_{le} \right).$$

Taking this one step further, consider the case where the two operating points discussed above represent the static state at two adjacent sample times, t and t+T_s. The state is dependent on the injections, so the driver for the difference in the operating points is the change in the injections. We model this change with a vector that is the sum of a deterministic part ΔΓ[t] and a nondeterministic part representing the process noise, $\mathbf{w}_{pn}$[t]:

$$\mathbf{x}[t+T_s] - \mathbf{x}[t] = -\mathbf{J}^{-1} \left(\Delta\Gamma[t] + \mathbf{w}_{pn}[t] + \mathbf{w}_{\mathrm{ln}} \right)$$

We consolidate both noise terms into a single variable, **w**[t], and solve for the future state, giving the state change as

$$\mathbf{x}[t+T_s] = \mathbf{x}[t] - \mathbf{J}^{-1} \left(\Delta\Gamma[t] + \mathbf{w}[t] \right). \quad (15)$$

Although the effect of **w**[t] becomes more significant as the change in real and reactive power injections increase between time steps, it provides a consistently accurate directionality for the change in state. In this model the main driver of change in state from one sampling instant to the next is the uncertain demand change.

$$\mathbf{u}[t] = \Delta\Gamma[t] = \Gamma[t+T_s] - \Gamma[t] \quad (16)$$

The effects of w[t] are discussed below.

B. Kalman Filtering

The Kalman filter can be thought of as static estimation with the following modifications: the prediction step is equivalent to the calculation of a set of pseudo-measurements representing the future state. The correction step is equivalent to the static estimation where both the normal measurements and the pseudo-measurements are incorporated into the measurement vector. The Kalman filter can by applied to a nonlinear plant through linearization of the measurement function and state prediction functions and implementing the Kalman filter as if they were linear. This method is known as the EKF.

The EKF is implemented for our system using the following four steps:

1) Predict the next state:

$$\overline{\mathbf{x}}[t+T_s] = \hat{\mathbf{x}}[t] + \mathbf{J}^{-1}\Gamma[t], \quad (17)$$

Where $\hat{\mathbf{x}}[t]$ is the estimated state at time t.

2) Calculate the Kalman Gain:

$$\mathbf{L}(t+T_s) = \left[\mathbf{S}(t) + \mathbf{J}^{-1}\mathbf{W}\left(\mathbf{J}^{-1}\right)^T \right] \mathbf{H}^T \left\{ \mathbf{H}\left[\mathbf{S}(t) + \mathbf{J}^{-1}\mathbf{W}\left[\mathbf{J}^{-1}\right]^T \right] \mathbf{H}^T + \mathbf{R} \right\}^{-1} \quad (18)$$

where $\mathbf{S} = E\left[(\mathbf{x}-\hat{\mathbf{x}})(\mathbf{x}-\hat{\mathbf{x}})^T \right]$ and $\mathbf{W} = E\left[\mathbf{w}\mathbf{w}^T \right]$ is assumed to be diagonal.

3) Use the measurement residual to correct the estimate:

$$\hat{\mathbf{x}}[t+T_s] = \overline{\mathbf{x}}[t+T_s] + \mathbf{L}[t+T_s]\left\{ \mathbf{z}[t+T_s] - \mathbf{h}(\overline{\mathbf{x}}[t+T_s]) \right\}. \quad (19)$$

4) Update the state covariance matrix:

$$\mathbf{S}[t+T_s] = \left(\mathbf{I} - \mathbf{L}[t+T_s]\mathbf{H} \right)\left(\mathbf{S}[t] + \mathbf{J}^{-1}\mathbf{W}\mathbf{J}^{-T} \right)\left(\mathbf{I} - \mathbf{L}[t+T_s]\mathbf{H} \right)^T + \mathbf{L}[t+T_s]\mathbf{R}\mathbf{L}^T[t+T_s] \quad (20)$$

The IKF expands on the EKF by using the following iteration for the update step

$$\hat{\mathbf{x}}^{k+1}[t+T_s] = \overline{\mathbf{x}}[t+T_s] + \mathbf{L}[t+T_s] \left\{ \mathbf{z}[t+T_s] - \mathbf{h}(\hat{\mathbf{x}}^k[t+T_s]) - \mathbf{H}\left(\overline{\mathbf{x}}[t+T_s] - \hat{\mathbf{x}}^k[t+T_s] \right) \right\} \quad (21)$$

Similar to (7), the iteration is complete when the applicable stopping criterion (8) is reached.

The IKF attempts to improve on the EKF performance, but because of the nonlinearities of the plant, neither the EKF nor the IKF can guarantee optimal estimation.

The technique described in this paper extracts a subset of the measurements, the real and reactive power injections Γ, and uses the changes in their values to generate an input vector. This, in conjunction with the dynamic model (15), allows for the prediction step.

The IKF uses the four-step method described by (17), (18), (21), and (20). The input is the change in the forecasted injections.

C. Simulations without noise

To give a baseline for comparison to an ideal estimate, the static estimator with the aforementioned stopping criterion is applied to the IEEE 14-bus test system in a noiseless environment. Without measurement noise, all state estimation error is due to the nonlinearities in the system and the numerical precision of the calculations. This simulation provides a lower bound for the estimation errors can be expected.

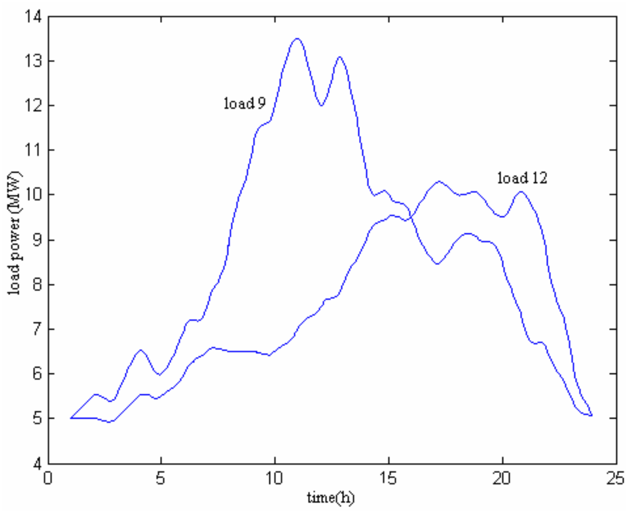

Fig. 2 Load profiles for busses 9 and 12

The 14-bus system is evaluated over a 24-hour period with snapshots occurring at 15 minute intervals. Time-varying real power loading is applied to busses 9 and 12 with bus 1 picking up the additional generation load. Plots of the loads are shown in Fig. 2.

To generate the forecast data for the prediction steps used by the Static with Load Forecast and Kalman Filter estimators, the simulations use the actual injections without any noise corruption. This information could alternatively come from the load forecast or other load prediction mechanisms. The covariance of the input error is assumed large to account for prediction error due to the nonlinearity of the system. A variance of 100 is used for this example.

For the Kalman Filter estimator, the power injection Jacobian, **J**, is calculated each hour (i.e., at every fourth time step). We found that calculating the injection Jacobian once an hour did not differ significantly from computing it at every time step.

For all simulations, the stopping criterion for the iterations are $\varepsilon=10^{-3}$ (angle in radians and magnitude in p.u.) and maximum K = 7. In the simulations run for this paper, the maximum iterations were reached in less than 5% of the samples. The measurement Jacobian, **H**, is calculated at each time step.

For a given simulation, the average sum-of-squared-errors state estimates from the true state at each time step is given as a metric for comparing the algorithms. These values are summarized in Table I for the busses in direct line from bus 1 to 9 (busses, 2, 4, and 9).

TABLE I
AVERAGE SUM OF SQUARED STATE ERROR , NOISLESS MEASUREMENTS

Bus	VOLTAGE ANGLE, DEGREES	VOLTAGE MAGNITUDE, P.U.
2	0.00106	0.00026
4	0.00348	0.00026
9	0.00747	0.00022

Typical voltage angles for this simulation were 17 degrees (0.3 radians) or smaller and voltage magnitudes were within 0.05 p.u. of 1 p.u. From this basis we can see that the voltage angles and magnitudes converge to less than 0.1% of the state given the stated stopping criterion.

D. Simulations with additive white Gaussian noise

For this simulation, zero-mean Gaussian noise has been added to all measurements and the simulation is repeated 500 times to provide statistically significant results. The variances are assumed to be all equal to 0.1 radians and 0.1 p.u. for the purposes of this simulation. Figure 3 shows the average sum of squared error of the voltage angle for busses 2, 4, and 9. The solid red curve shows the performance of the static state estimator. Similarly the dashed green curve and the dotted blue curve show the performance of the augmented static state estimator and the dynamic state estimator respectively. To provide a metric for comparison, each curve is summarized in Table II by the average value of the curve (i.e., the average sum of squared error for all voltage angle estimates of a given bus).

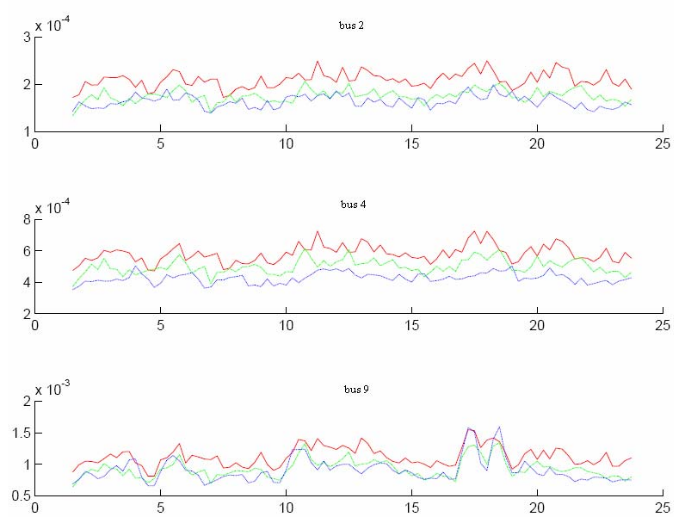

Fig. 3 Plots of average sum of squared voltage angle error for each time step. Solid red is static state estimator, dashed green is static state estimator with augmented measurements, and dotted blue is dynamic state estimator.

TABLE II
AVERAGE SUM OF SQUARED STATE ERROR AND PERCENT CHANGE FROM STATIC STATE ESTIMATION (VOLTAGE ANGLE, DEGREES)

Bus	Static	Static with Load	Kalman Filter

		Forecast	
2	0.0120	0.0105 (-16%)	0.0094 (-22%)
4	0.0333	0.0286 (-14%)	0.0245 (-27%)
9	0.0642	0.0532 (-17%)	0.0519 (-19%)

Similar to Figure 3 and Table II for voltage angle, Figure 4 and Table III show the sum of squared errors for the voltage magnitude on busses 2, 4, and 9.

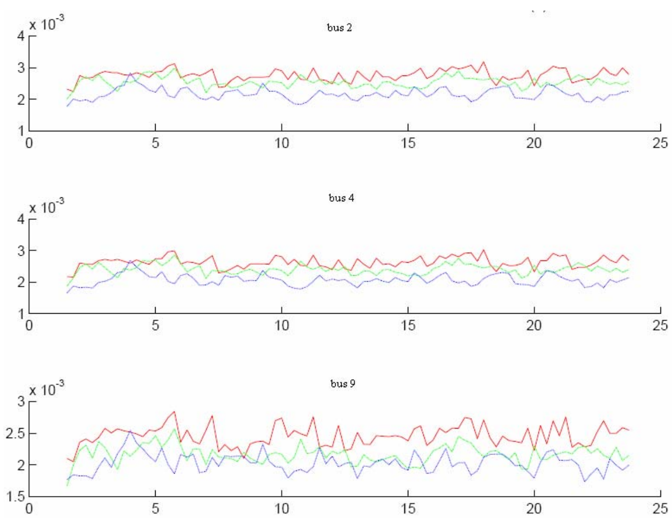

Fig. 4 Plots of average sum of squared voltage magnitude error for each time step. Solid red is static state estimator, dashed green is static state estimator with augmented measurements, and dotted blue is dynamic state estimator.

TABLE III
AVERAGE SUM OF SQUARED STATE ERROR AND PERCENT CHANGE FROM STATIC STATE ESTIMATION (VOLTAGE MAGNITUDE, P.U.)

Bus	Static	Static with Load Forecast	Kalman Filter
2	0.00276	0.00254 (-7.9%)	0.00217 (-22%)
4	0.00263	0.00240 (-8.6%)	0.00207 (-21%)
9	0.00246	0.00217 (-12%)	0.00203 (-17%)

IV. DISCUSSION

This paper puts forward the idea of combining the basic power flow equations of an electric power network with the load forecast to create a discrete-time dynamic model. In this model, changes of states, namely, voltage and phase angles, are caused by incremental changes in the load demand. This model is qualitatively different from the models currently used by the system operators in which state estimators are strictly static, and load forecasts are not directly used for state estimation. The information about the load forecast is particularly important when the load changes significantly. We use this model to implement a discrete-time Kalman filter for state estimation. The preliminary results show potential benefits from incorporating load forecasts into the state estimation.

The simulations that were run using the static state estimation algorithms with the augmented measurement vector show significant improvements over the static state estimator using measurements alone. This is expected as providing more and accurate information to a proven method should always result in an improvement.

The simulations that were run using pseudo-dynamics and Kalman filtering show consistent and significant improvement over both methods of static state estimation. This is significant in that the only additional information used by the dynamic state estimator over the augmented static state is the pseudo-dynamic model and the previous state estimate.

In addition to demonstrating higher accuracy, the dynamic state estimator requires slightly less computation than the augmented static state estimator due to the smaller size of the measurement vector and associated measurement Jacobian.

Future work will combine this approach with dynamic load estimation algorithms currently under development [10].

V. ACKNOWLEDGMENTS

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VII. Biographies

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Bruce Krogh (M'83–SM'94–F' 98) received the B.S. in mathematics and physics from Wheaton College, Wheaton, IL, in 1975 and his Ph.D. in electrical engineering from the University of Illinois at Urbana-Champaign in 1983. He joined Carnegie Mellon University, Pittsburgh, PA, in 1983 where he is a professor of electrical and computer engineering.

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