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Kalman Filter Based Electricity Market States Forecasting: A State-Space Framework

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***Abstract*—Gaining money and high profit is the dream of electricity market investors; however, it requires accurate financial knowledge and price forecasting ability. Most of the investors are used the electricity market historical information for forecasting power generation, consumption, and utility price. Unfortunately, electricity market time-series profile is high volatility and change over time, so the factual data cannot accurately reflect the electricity market states such as power consumption and generation. In the literature, there is no systematic way or suitable models that can fit, analyze, and predict electricity market system states over time. Interestingly, this paper proposes an electricity market state-space model which is obtained by a set of electricity market differential equations. After simplifying of these equations, the continuous-time electricity market state-space model is derived. Using discrete-time step size parameter, the continuous-time system is discretised. Furthermore, the noisy measurements are obtained by a set of smart sensors. Finally, the Kalmna filter based electricity market state forecasting algorithm is developed based on noisy measurements. Simulation results show that the proposed algorithm can properly forecast the electricity market states. Consequently, this kind of model and algorithm can help to develop the electricity market simulator and assist investor to participate/invest electricity market regardless of the world economic downtown.**

***Index Terms*—Energy consumption, Kalman filter, price forecasting, power generation, state-space electric market.**

I. Introduction

Electricity market participant is generally trying to forecast power generation, consumption, and utility price so that they can invest money and time to the utility market for maximizing profit. Without a reliable forecasting technique, adequate knowledge, and bidding strategy, the personal and company owners can lose money in the competitive electricity market. Generally speaking, most of the investors are used the historical data for forecasting customer load, demand, and price. Unfortunately, the market data are the mostly noisiest and intermittent in nature [1]. Therefore, forecasting the electricity market states such as power consumption and demand cannot accurately reflect the real-time need. In fact, storage of huge amount of power is very difficult, and it can lose money, and dream [2]. Basically, there is no systematic way to develop electricity market model and it states cannot be predicted without using market data. This paper proposes a state-space electricity market model, and the Kalman filter is designed for forecasting it states.

An electricity market is a real-time place of high revenue to the investors where they are used different algorithms for predicting the market conditions. To begin with, the extended Kalman filter (EKF) for the Japan electricity market price forecasting is proposed in [3]. In this approach, a time-varying autoregressive model is adopted for price forecasting. Moreover, the derivative-free EKF scheme is used for price forecasting of electricity market [4], [5]. It uses the Black-Scholes electricity market model for price forecasting. However, the forecasting algorithm requires a transformation of the initial price dynamics into a state-space model of the linear canonical form. Generally speaking, the electricity market assets value and volatility are not directly measurable [6]. Therefore, by forecasting the electricity market value of the utility company, it becomes possible to forecast the firm's distance to default [6]. Then the forecasted electricity market value of the utility company is used to determine bankruptcy risk and the probability of default [6].

Furthermore, the day-ahead electricity price forecasting using the KF is presented in [7]. In this scheme, the state transition matrix of the electricity market model is obtained using the regression approach. Unfortunately, the training date is based on the America PJM historical data which may be unreliable or inaccurate [1]. Additionally, the H-infinity and KF algorithms are adopted for short term electricity market price forecasting where the system model is designed based on regression analysis using the California ISO data [8]. For application point of view, the KF algorithm is used for cyber physical systems [9], [10]. The reliable and secure communication requirement of smart grid is presented in [11].

From the machine learning point of view, the multi-layer back-propagation and neuro fuzzy schemes are adopted for predicting electricity market clearing price [12], [13]. Combining with the support vector machine and wavelet transform, the designed scheme is used for predicting the electricity price. Likewise, energy forecasting using the long short-term memory and gated recurrent unit (deep neural network staffs) is proposed in [14]. Using spark cluster, the algorithm is tested, and it shows that the gated recurrent unit provides better load forecasting accuracy compared with the long short-term memory. Finally, evolutionary ensemble long short-term memory machine learning method is proposed for customer peak electricity demand prediction [2], [15]. Basically, the testing, training, and validation datasets are used in this work based on empirical experimental results.

None of the approaches for price forecasting are developed an appropriate state-space model without considering historical profile. Generally, financial time-series data is highly noisy, non-seasonal, irregular, and chaotic in nature. Driven by this motivation, this paper proposes a state-space electricity market model, and the KF is designed for forecasting it states. The main contributions of the paper are summarized as follows:

- Proposed a state-space electricity market model which is obtained by simplified a set of partial differential equations.
- Proposed an optimal power generation, consumption and price forecasting algorithm.

The rest of the article is organised as follows. The proposed system model is presented in Section II. The KF algorithm is described in Section III, which follows simulation results and conclusion.

II. Electricity Market State-Space Framework

According to Alvarado scheme (one-supplier one-consumer), the differential equations of electricity market are given by [16], [11]:

$$\dot{P}_g = (\lambda - c_g P_g - hP_e - b_g)/\tau_g. \tag{1}$$
$$\dot{P}_d = (c_d P_d + b_d - \lambda)/\tau_d. \tag{2}$$
$$\dot{P}_e = P_g - P_d. \tag{3}$$
$$\dot{\lambda} = -P_e/\tau_\lambda. \tag{4}$$

Here, P_g, P_d, and P_e are the generated power, consumed power, and difference between power demand and supply, λ is the electricity price, τ_g, τ_d, τ_λ are the supply, demand, and price controlling parameters, c_g, b_g, c_d, and b_d are the time constants related to power supply and consumption, and hP_e is the additional cost paid by the supplier when there is excess supply or demand [17], [18].

The aforementioned system of equations can be written as a compact form as follows:

$$\dot{\mathbf{x}} = \mathbf{F}_c\mathbf{x} + \mathbf{G}_c\mathbf{u}. \tag{5}$$

Here, $\mathbf{x} = [P_g,\ P_d,\ P_e,\ \lambda]'$ is the electricity market state vector, $\mathbf{u} = [b_g\ b_d\ 0\ 0]'$ is the system input vector, the electricity market state matrix $\mathbf{F}_c$, and the system input matrix $\mathbf{G}_c$ are derived by: $\mathbf{F}_c = \begin{bmatrix} -c_g/\tau_g & 0 & -h/\tau_g & 1/\tau_g \\ 0 & c_d/\tau_d & 0 & -1/\tau_d \\ 1 & -1 & 0 & 0 \\ 0 & 0 & -1/\tau_\lambda & 0 \end{bmatrix}$, $\mathbf{G}_c = diag[-1/\tau_g,\ 1/\tau_d\ 0\ 0]$. Using sampling interval μ, the aforementioned system is discretised as follows:

$$\mathbf{x}_{t+1} = \mathbf{F}\mathbf{x}_t + \mathbf{G}\mathbf{u}_t + \mathbf{n}_t. \tag{6}$$

Here, $\mathbf{F} = \mathbf{I} + \mu\mathbf{F}_c$, $\mathbf{G} = \mu\mathbf{G}_c$, t is the discrete time, and $\mathbf{n}$ is the Gaussian noise whose covariance matrix is assumed to be $\mathbf{Q}$.

The observation information from the independent system operator is obtained as follows:

$$\mathbf{z}_{t+1} = \mathbf{H}\mathbf{x}_t + \mathbf{w}_t. \tag{7}$$

Here, $\mathbf{H}$ is the observation matrix, and $\mathbf{w}$ is the measurement noise whose covariance matrix is assumed to be $\mathbf{R}$.

III. Proposed Electricity Market State Forecasting Algorithm

For power generation and consumption forecasting, we are adopted the KF algorithm. Technically, the KF operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. It has two steps: state prediction and correction. The prediction step produces estimates of the current state variables along with their uncertainties [19], [20]. The correction step is updated the estimate of the current state variables using a weighted average, with more weight being given to estimates with higher certainty [21], [22], [23]. The prediction step is given by [24], [25]:

$$\hat{\mathbf{x}}_{t|t-1} = \mathbf{F}\hat{\mathbf{x}}_{t-1|t-1} + \mathbf{G}\mathbf{u}_t. \tag{8}$$
$$\mathbf{P}_{t|t-1} = \mathbf{F}\mathbf{P}_{t-1|t-1}\mathbf{F}' + \mathbf{Q}. \tag{9}$$

Here, $\hat{\mathbf{x}}_{t|t-1}$ and $\mathbf{P}_{t|t-1}$ are the prediction state and error covariance while $\hat{\mathbf{x}}_{t-1|t-1}$ and $\mathbf{P}_{t-1|t-1}$ are their corresponding initial values. The correction step is given by [26], [27] [28]:

$$\hat{\mathbf{x}}_{t|t} = \hat{\mathbf{x}}_{t|t-1} + \mathbf{K}_t[\mathbf{z}_t - \mathbf{H}\hat{\mathbf{x}}_{t|t-1}]. \tag{10}$$
$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}'(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}' + \mathbf{R})^{-1}. \tag{11}$$
$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{K}_t\mathbf{H}\mathbf{P}_{t|t-1}. \tag{12}$$

Here, $\hat{\mathbf{x}}_{t|t}$ and $\mathbf{P}_{t|t}$ are the updated state and error covariance, and $\mathbf{K}_t$ is the estimation gain.

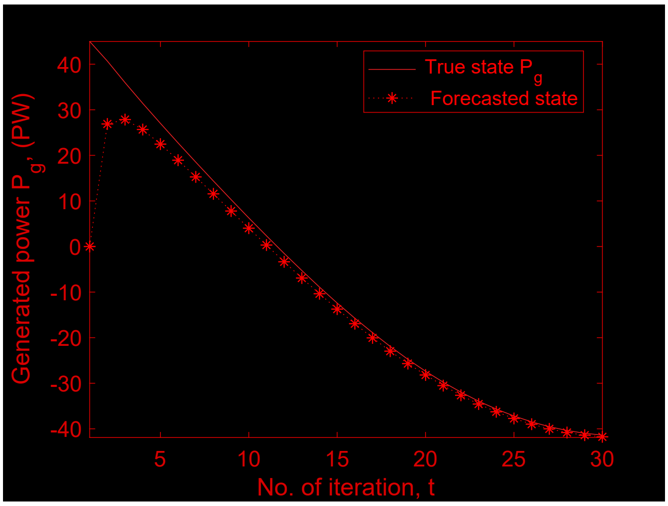

Fig. 1: Original power generation and it forecasting without sensor fault condition.

TABLE I: Electricity Market Simulation Parameters.

Symbols	Values	Symbols	Values
τ_g	0.2	c_g	0.1
b_g	2	τ_d	0.1
c_d	-0.2	b_d	10
τ_λ	100	h	0.1
$\mathbf{Q}$	0.0001*$\mathbf{I}$	$\mathbf{R}$	0.002*$\mathbf{I}$
μ	0.12 sec		

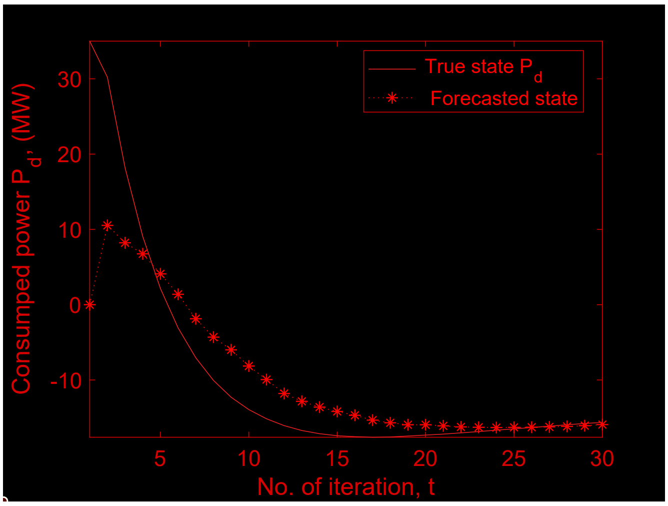

Fig. 2: Original power consumption and it forecasting without sensor fault condition.

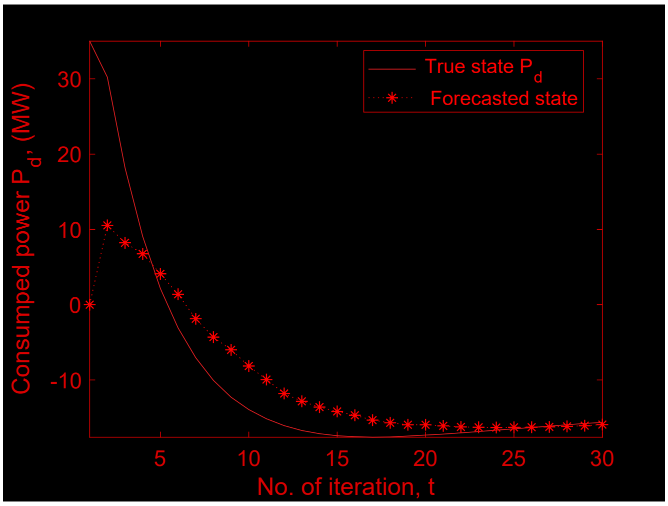

Fig. 4: Schedule price and it forecasting without sensor fault condition.

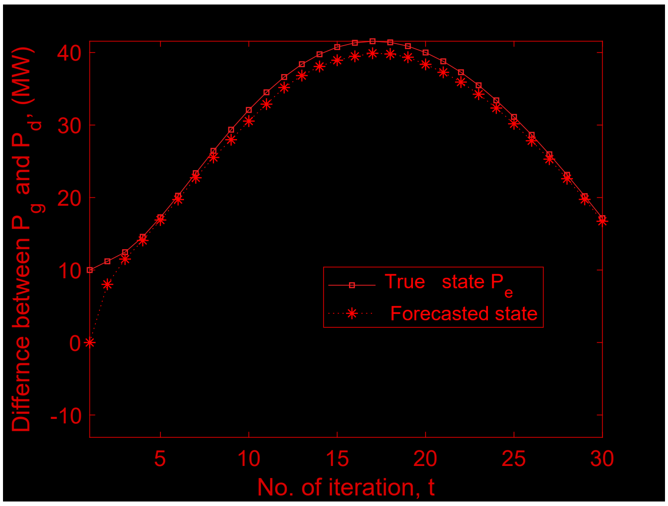

Fig. 3: Power imbalance and it forecasting without sensor fault condition.

IV. Simulation Results and Discussions

The simulation parameters are shown in Table I [16], [11]. The process and measurement noises are independent with the system state and measurement. The discrete time step size parameter μ is 0.12 seconds, and other parameters are used based on experience. Based on the measurement, the Kalman filter is predicted and corrected the electricity market system states over time.

The simulation results are presented in Figs. 1-4. For example, Fig. 1 shows the generated power versus forecasted one, it can be seen that the Kalman filter can able to properly forecast power generation pattern within 30 iterations, i.e., 3.6 seconds (iteration t *step size parameter μ=30*0.12). This is due to the fact that the Kalman filter can able to find optimal gain for properly forecasting the state. Fig. 2 illustrates the actual power consumption versus forecasted state. Clearly, it requires around 3 seconds (iterations *μ=25*0.12) to accurately forecast power consumption. Moreover, the difference between power generation and consumption is demonstrated in Fig. 3. Finally, the utility price and its forecasted state is depicted in Fig. 4. Obviously, it provides the consistency price forecasting accuracy.

V. Conclusion and Future Work

The paper proposes an electricity market state-space model where measurements are obtained by a set of sensors. These measurement units are corrupted by noises. Then the power consumption, generation, and price forecasting algorithm is proposed. Specifically, we are adopted the Kalman filter for electricity market system states forecasting based on designed model (without historical data). Numerical results show that the proposed method can properly forecasting the electricity market states within 3.6 seconds. In future, we will develop distributed electricity market state forecasting algorithm considering cyber attacks and packet loess. Also, we will develop a state-space electricity market model considering multiple participants and utilities.

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