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Application of Kalman Filtering for PV Power Prediction in Short-Term Economic Dispatch

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ABSTRACT

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The aim of this thesis is to predict the short-term power production of PhotoVoltaic (PV) power plants for the economic dispatch problem with the help of Kalman filtering. The Economic Dispatch (ED) problem in power systems is known as an optimization problem in which the cost of producing energy to reliably supply consumers is minimized, hence the power production is assigned to all the generating units that are dispatchable. Because of the generation cost of renewable energy such as PV is relatively low, it is advantageous to utilize. However, these resources are intermittent. These renewable resources bring a lot of uncertainty into the power system, their power cannot be pre-specified due to their weather dependent properties and therefore it is a big challenge to include them in the ED problem.

For this reason, the work in this thesis will focus on developing a predictive model built on Kalman Filtering for the short-term PV prediction. The model first predicts the solar irradiance and temperature based on an initial guess at each time period. Then, the Kalman filter will refine the results using sensor measurements so that the final estimated outputs from this filter can be used for better prediction in the next period. The PV electric power is then calculated since it is a function of irradiance and temperature.

The proposed methodology has been illustrated using the IEEE 24-bus reliability test system. The real data from National Renewable Energy Laboratory is used in this thesis as the actual outputs that the outputs of the predicting model should get close to. Finally, the performance of the proposed approach is obtained by comparing its results with the results from an available method called the persistent prediction method.

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Chapter 1

Introduction

Economic Dispatch (ED) in power systems is an optimization problem in which the cost of producing energy to reliably supply consumers is minimized. Because the costs of power production are different for different generators, ED determines electricity outputs of each generator so that the total power generated will meet the load of the system at the lowest cost possible without violating any transmission and operational constraint. The amount of power scheduled for each generator from economic dispatch are called the economic set points where the whole system operates at the minimum cost. If the generators are dispatchable (the outputs can be controlled) and the loads are known, then the economic dispatch problem can be solved by various optimization methods. However, the loads and generators in reality are more complicated and have a lot of constraints as well as uncertainty that need to be taken into account.

In recent years, renewable energy resources (RERs) have been rapidly increasing and expected to continue in the future [1] [2] .They are sustainable, environmental friendly but also variable as their electrical power depends on the weather. The high penetration of RERs in power systems has brought a big challenge to the unit commitment and economic dispatch problems. These RERs are uncertain and non-dispatchable because of their weather dependent property. This uncertainty makes it hard to solve the dispatch problem when the exact electric power generated by these unit is unknown and cannot be controlled at a certain level. The simplest solution is that these RERs are treated as negative loads and there will be reserve units to compensate in case of insufficient power generated from them.

However, the better solution but hard to obtain is to predict the output of these RERs. The closer the prediction is, the better the optimal solution for dispatch problem will be. Understanding the necessity of power prediction for renewable resources in economic dispatch problem, many approaches have been introduced to predict the power of RERs or to bound the uncertainty so that ED can be run without too much risk.

The work of this thesis is to predict short-term power of photovoltaic (PV) power plants, be a part of the on-going research in ED under uncertainty. The thesis is organized as follows. A literature survey will be given in Chapter 2. The background on energy market, cost of generators and economic dispatch problem with and without losses will be described in Chapter 3. Next, in chapter 4, a predicting model for solar irradiance and temperature built on a Kalman filter approach is introduced. Chapter 5 will present the results of a case study with IEEE 24-bus system that is modified to include 2 PV generators. Finally, concluding remarks will be given in Chapter 6.

Chapter 2

Literature survey

The benefits of renewable energy on decreasing the fuel cost and better environmental effect have led to the rapid increase of wind and solar energy in power systems. At the same time, it brings the uncertainties into the systems and results in a significant challenge to the operation of the systems, especially the economic dispatch problem. Many optimization methods have been proposed to handle these uncertainties and can be divided into two main categories: 1) Deterministic Optimization, and 2) Stochastic Programming.

The deterministic approach with the robust optimization has received attention recently because of its ability to handle uncertainty by pre-determining the uncertainty sets. Reference [3] proposed an adaptive robust optimization for the security constrained unit commitment problem. The model takes into account the load variance by constructing a deterministic uncertainty set based on the mean and the range of the uncertainty data.

$$\mathcal{D}^t(\bar{\boldsymbol{d}}^t, \hat{\boldsymbol{d}}^t\ \Delta^t) := \left\{ \boldsymbol{d}^t \in \mathbb{R}^{N_d} : \sum_{i \in \mathcal{N}_d} \frac{|d_i^t - \bar{d}_i^t|}{\hat{d}_i^t} \leq \Delta^t\ ;\ d_i^t \in \left[\bar{d}_i^t - \hat{d}_i^t, \bar{d}_i^t + \hat{d}_i^t\right], \forall i \in \mathcal{N}_d \right\}$$

Where:

$\mathcal{D}^t$: The uncertainty set at time *t*

$\boldsymbol{d^t}$= ($d_i^t, i \in \mathcal{N}_d$): vector of net injection at time *t*

$\bar{d}_i^t$: the nominal value of the net injection of node *i* at time *t*

$\hat{d}_i^t$: the deviation from the nominal net injection value of node *i* at time *t*

$\mathcal{N}_d$: the set of nodes that have uncertain injections, N_d is the number of such nodes

Δ^t: the “budget” of uncertainty

This approach basically bounds the uncertainty of the load injection $\boldsymbol{d^t}$ within the maximum deviation $\widehat{\boldsymbol{d}}^{\boldsymbol{t}}$ from the nominal value $\overline{\boldsymbol{d}}^{\boldsymbol{t}}$ and adjusts the range of the deviation using budget $\Delta^{\boldsymbol{t}}$(range from 0 to 1 for each node, and 0 to N_d for the total N_d nodes). In every time period *t*, the upper and lower bounds are independent of those in the earlier period and that is why it is called static uncertainty set. Obviously, this budget determines the range of the uncertainty bound and therefore the choice of this budget level will affect the result of the optimal solution. In order to understand the effect of the budget choice, the authors conducted tests with budget $\Delta^{\boldsymbol{t}}$ varied from 0 to N_d and observed that the best performance of the robust solution might be obtained when the budget is chosen using central limit theorem as a guideline ($\Delta^{\boldsymbol{t}} \sim O(\sqrt{N_d})$) and practical criteria in real-life. A similar approach using uncertainty budget is also introduced in [4] for wind power output. A deterministic model for economic dispatch problem is also developed based on this adjustable uncertainty budget and once again, different levels of budget selected results in different performances of the optimal solution. Determining the uncertainty bound is an important factor. The smaller this bound is, the more effecting is the result. That is why prediction is important.

On the other hand, the approach of stochastic methods is naturally related to the characteristic of wind and solar generation and therefore it has also been investigated concurrently with the deterministic approach. In reference [5], a scenario-based and fuzzy self-adaptive learning particle swarm optimization is used to solve the economic dispatch problem considering load and wind power uncertainties. This approach handles the uncertainties by generating scenarios using roulette wheel technique on the basis of probability distribution function. The stochastic uncertainties are now decomposed into equivalent deterministic scenarios and the proposed algorithm goes through the entire search space using particle swarm optimization to find the best, mean and worst costs associated with the generated scenarios. A similar approach using probabilistic envelop is also used in [6] for load uncertainties. The deviation of load injection envelops in time and create a scenario tree, and the economic dispatch problem is solved based on this tree.

Another approach introduced in [7] and [8] tries to predict the future short-term outputs of wind generators by forecasting wind speed using spatio-temporal model. The authors applied the Trigonometric Direction Diurnal (TDD) Model proposed in [9] to model wind speed. Wind speed in the next period V_{t+1} of TDD model is assumed to follow a truncated normal distribution on the nonnegative real domain: $V_{t+1} \sim N^{+}(\mu_{t+1}, \sigma_{t+1})$.

Where:

V_{t+1}: wind speed at time period $t+1$

$N^+(\mu_{t+1}, \sigma_{t+1})$: normal distribution at time $t+1$ with mean μ_{t+1} and covariance σ_{t+1}

This model basically tries to predict the central parameter μ_{t+1} and scale parameter σ_{t+1} by using trigonometric functions on the historical data (*h* periods earlier) of local and nearby windfarms. The wind power in near future is calculated based on this predicted wind speed and will be used later on to solve the *k*-step ahead economic dispatch of the system.

Inspired by this spatio-temporal wind forecast, the authors in [10] propose a method to construct linear dynamic uncertainty sets for wind power using statistical inference techniques from time series analysis. These dynamic uncertainty sets capture the correlation between uncertain resources and the evolution of uncertainty over time of each uncertain resource. The stochastic model for available power of a renewable generator at time *t* is $\tilde{p}_t = f_t + \tilde{u}_t = f_t + \sum_{l=1}^{L} A^l \tilde{u}_{t-l} + \tilde{\varepsilon}_t$

Where:

$\tilde{p}_t$: power of a renewable generator at time *t*

f_t: pre-estimated power of that renewable generator at time *t*

$\tilde{u}_t = \sum_{l=1}^{L} A^l \tilde{u}_{t-l} + \tilde{\varepsilon}_t$: deviation from f_t.

L: periods of time lag before *t*

A^l: correlation matrix between $\tilde{u}_t$ and $\tilde{u}_{t-l}$

$\tilde{\varepsilon}_t$: random variable

The deviation $\tilde{u}_t$ is the residual of the power at time *t* involving from *L* periods earlier plus the random variable $\tilde{\varepsilon}_t$ with mean 0 and covariance matrix Σ. The matrices A^l and Σ can be estimated using statistical methods developed for time series. In other words, at each time period, unlike the fixed uncertainty sets in [3] , these sets can change as they are functions of uncertainty realization in previous time periods. The authors later on completed this concept of dynamic uncertainty sets for both wind and solar power uncertainties in [11].

Following up on this research, the work in this thesis tries to predict the short-term power of photovoltaic (PV) power plants using a prediction model built on Kalman filter. The model first predicts the solar irradiance and temperature based on an initial guess at each time period. Then, the Kalman filter will refine the results using sensor measurements so that the final estimated outputs from this filter can be used for better prediction in the next period. The PV electric power can be calculated after that as it is a function of irradiance and temperature.

Chapter 3

Background

3.1 Electricity market

Electricity market is the place where electricity is sold, bought and traded. The market can be split into wholesale and retail markets. In the wholesale market, the purchase and sell are made between generators and other resellers who intend to sell the power to someone else. The amount of energy trading is large and usually measured by Mega Watts. The purchase and sell of electricity to the end users are done in the retail market, usually in Kilo Watts.

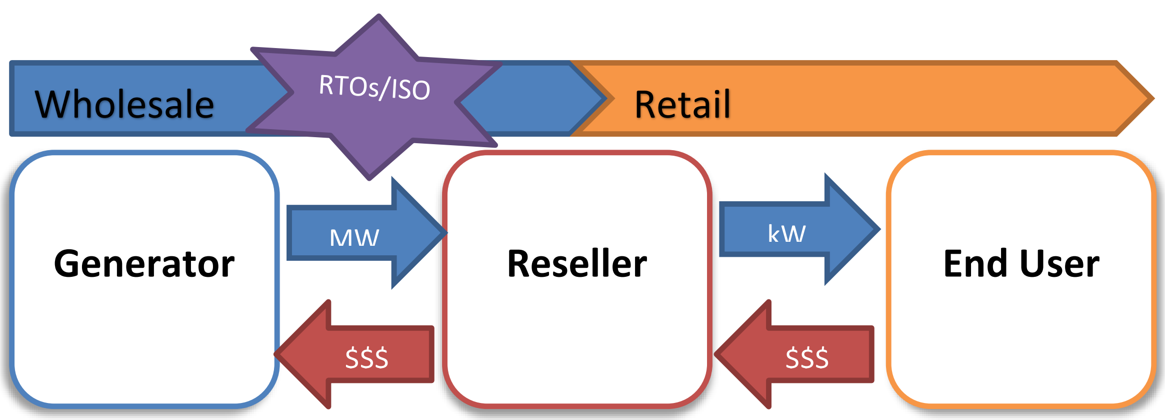

Figure 1: Electricity Market - Wholesale and Retail

Regional Transmission Organizations (RTOs) or Independent System Operators (ISOs) are the third-party who is responsible for the operation of the transmission system. Because of the inevitable inherent interest of a company who could own all of the distribution system, transmission system and some generators, these independent operators make sure the fairness of the power dispatch that includes both utility-owned generators and competitive generators. ISO/RTOs work for the benefit of consumers by providing impartial transmission access to facilitate competition. There are ten major RTO/ISOs in North America.

- ISO New England
- New York ISO
- PJM (Mid-Atlantic, a portion of Midwest)
- Midwest ISO
- Southeast Power Pool
- ERCOT (most of Texas)
- California ISO
- Alberta Electric System Operator
- Ontario Independent Electricity System Operator
- New Brunswick System Operator

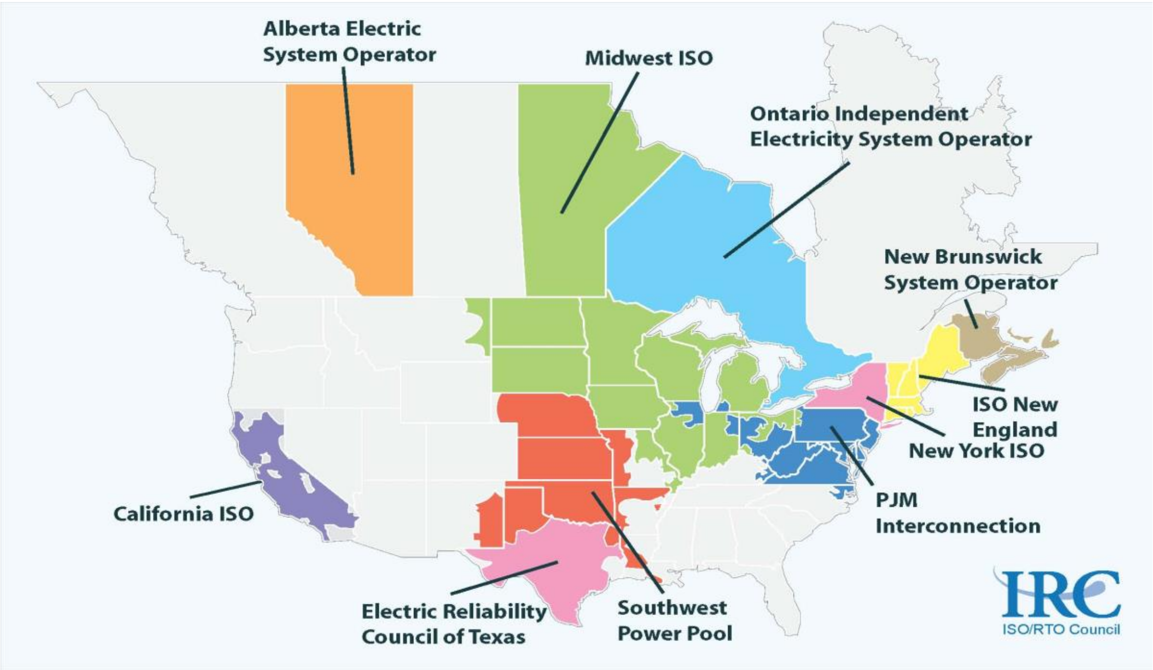

Figure 2: Ten majors ISO/RTOs in North America (source: IRC)

These ISO/RTOs also conduct what is called day-ahead and real-time markets. In day-ahead market, participants sell and purchase electric energy by placing their bids and offers for the following day. According to the information collected, the prices are calculated hourly to make the binding schedule of commitments (unit commitment). On the other hand, real-time market is based on the actual condition of the system at that particular time to calculate the prices every 10-15 minutes (economic dispatch) and therefore the prices can be volatile.

3.2 Cost of electricity production and auction-based market

In both day-ahead and real-time market, at a specific time period, the total load of the system is forecasted, the generators that are online and ready to dispatch power to the system are known. Then the economic dispatch is the process of finding the optimum operating points of those generators such that the cost of total power dispatch is minimum. In order to do that, the cost of producing energy of each generator has to be specified.

3.2.1 Costs of a generator.

Production cost: is the cost when a generator is operating to produce energy. Depends on what kind of generator (thermal, nuclear, hydro, solar wind…), the production cost will be variable. For example, a thermal unit needs heat to boil water and run the turbine. That heat is gotten by burning fuel and it cost money. Each thermal generator has its own heat rate characteristic and therefore the cost for each MW electricity produced will be different.

No-load cost: Once a generator connected to the system, it needs to be kept online to be ready to dispatch even though there is no load because it takes time to bring it online and the cost is significant.

Start-up cost: the cost that is needed to bring the unit online and connect to the system. A unit can start from different states (cold, medium, hot) and each state will cost differently.

Shut-down cost: cost to shut down the unit.

Other cost: maintenance, operating, crew expenses…

After considering all the costs that a generator can incur. A general cost function of a generating unit can be represented by a quadratic form.

$$C_i(P_{Gi}) = \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 \text{ (\$/h)} \tag{3.1}$$

Where:

$\alpha_i, \beta_i\ \gamma_i$: cost coefficients of unit *i*.

P_{Gi}: power generated by unit *i*.

$C_i(P_{Gi})$: operating cost of unit *i* at P_{Gi}.

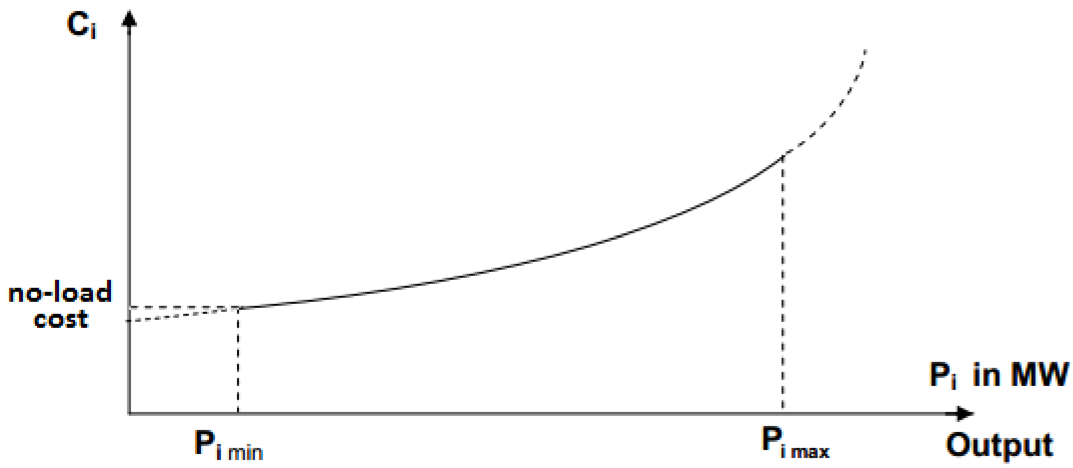

Figure 3: Cost curve of a power generating unit

3.2.2 Auction-based trading.

In the auction-based trading, suppliers bid the prices corresponding with the amount of MW electricity that they want to sell. Similarly, the consumers offer the prices that they are willing to pay for the corresponding amount. The object is to match the bids and offers for the most efficient transaction. The relationship can be described under the economic terms.

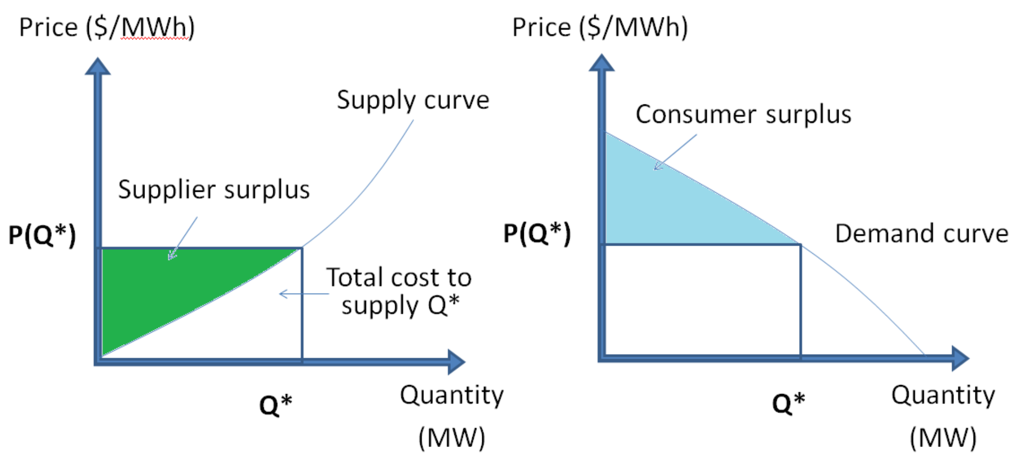

Figure 4: Supply curve and demand curve

The suppliers want to be paid no less than the supply curve to produce the next increment MW. The consumers are willing to pay no more than demand curved to consume the next increment MW. **Supplier surplus** is the extra revenue above what is required to produce the quantity Q*. **Consumer surplus** is the benefit the consumers save to consume quantity Q*. When the total surplus is maximized, the clearing price is reached.

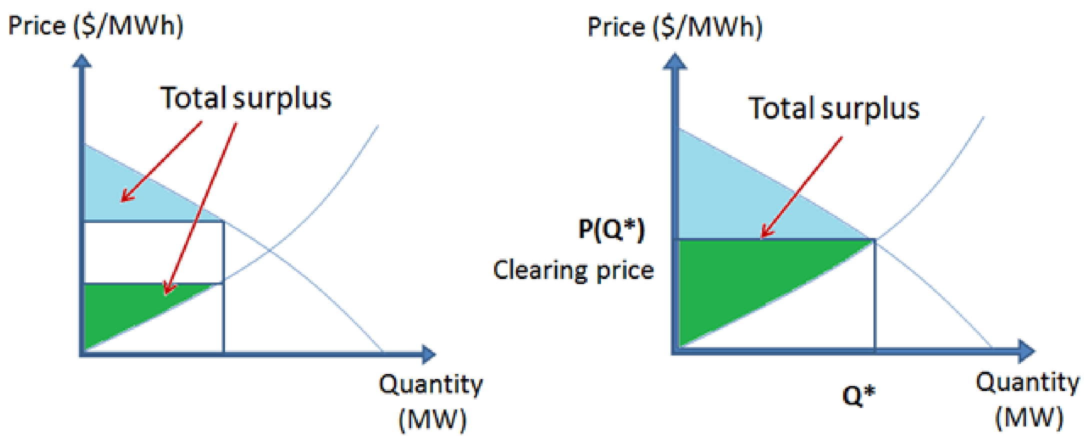

Figure 5: Clearing price after maximizing the total surplus.

The total system cost is also known as the negative of the total surplus. It means maximizing the total surplus will minimize the system cost.

3.3 Economic dispatch

The objective of economic dispatch problem is to find the economic set point of power generated by each generating unit so that the total cost of the system to supply the load is minimum.

3.3.1 Bus bar economic dispatch

In the bus bar economic dispatch, all the losses are neglected and there is no constraint on system transmission as well as generator outputs. The objective function of economic dispatch problem can be represented as follows:

$$\min_{P_{Gi}} C_T = \sum_{i=1}^{N} C_i(P_{Gi}) \tag{3.2}$$

Subject to:

$$\emptyset = \sum_{i=1}^{N} P_{Gi} - P_D = 0 \tag{3.3}$$

Where:

C_T: total cost of all generators.

N: Number of generators participating in the power dispatch.

$C_i(P_{Gi})$: cost function of generator *i*, obtained from (3.1).

P_D: total load of the system.

The solution of the objective function (3.2) is the operating economic set point P_{Gi}^* of each generator at which the total cost C_T of all generating units to supply the system load is minimum. Equation (3.3) described the power balance constraint where the total power generated is equal to total load, or in other word, the difference between the power generated and the load is zero.

By substituting (3.1) into (3.2), the objective function can be expanded to:

$$\min_{P_{Gi}} C_T = \sum_{i=1}^{N} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) \tag{3.4}$$

In order to handle the power balance constraint, an undetermined variable has been multiplied with the empty set of the power constraint function and embedded into (3.4):

$$\min_{P_{Gi},\lambda} C_a = \sum_{i=1}^{N} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) - \lambda \left(\sum_{i=1}^{N} P_{Gi} - P_D \right) \tag{3.5}$$

C_a is known as *Lagrange function* with *Lagrange multiplier* λ. The necessary conditions for C_a to have a minimum value is that the derivative of the Lagrange function with respect to each variable is equal to 0. The variables of Lagrange function are P_{Gi} and λ.

$$\frac{\partial C_a}{\partial \lambda} = \sum_{i=1}^{N} P_{Gi} - P_D = 0 \tag{3.6}$$

$$\frac{\partial C_a}{\partial P_{Gi}} = \frac{dC_i}{dP_{Gi}} - \lambda = 0 \tag{3.7}$$

Equation (3.6) is the derivative of C_a with respect to λ, as we can see, it gives back the power balance constraint in (3.3). This is the reason the evolution to Lagrange function is needed to establish the necessary conditions for the objective function C_T to have a minimum value and still be able to handle the constraint.

Equation (3.7) is the derivative of Lagrange function with respect to each power output variable P_{Gi}. By taking λ to the other side of the equation, we can observe that the incremental cost of all generating units is equal to λ, an undetermined variable. The incremental cost of a unit can be obtained like in figure 6.

$$IC_i = \frac{dC_i}{dP_{Gi}} = \lambda \tag{3.8}$$

In summary, the necessary for the objective function to have a minimum value is that all the generating units operate at the same incremental cost and the total power generated is equal to the total load of system.

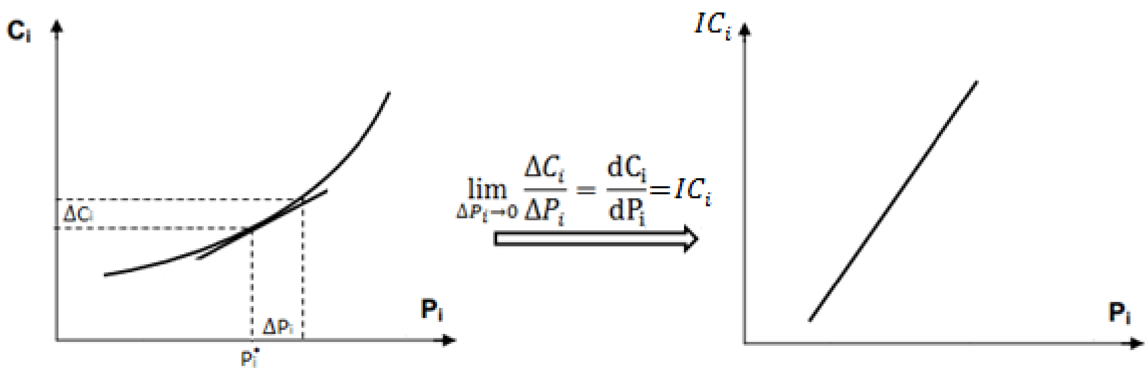

Figure 6: Incremental cost of a generating unit.

Example: Three generating units with the cost coefficients given in table 1.

Unit #	α	β	γ
1	561	7.92	0.001562
2	310	7.85	0.00194
3	78	7.97	0.00482

Table 1: Cost coefficients of 3 generating units

They are supplying a total load of 850 MW. Find the amount of power each unit should generate so that the total cost will be minimum.
The objective function of this problem would be:

$$\min_{P_{Gi},\lambda} C_a = \sum_{i=1}^{3}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) - \lambda\left(\sum_{i=1}^{3} P_{Gi} - P_D\right)$$

Or:

$$\begin{aligned}\min_{P_{G1},P_{G2},P_{G3},\lambda} C_a = {} & 561 + 7.92P_{G1} + 0.001562P_{G1}^2 \\ & + 310 + 7.85P_{G2} + 0.00194P_{G2}^2 \\ & +78 + 7.97P_{G3} + 0.00482P_{G3}^2 \\ & -\lambda(P_{G1} + P_{G2} + P_{G3} - 850) \qquad (3.9)\end{aligned}$$

The necessary conditions for (3.9) to have a minimum are:

$$\frac{\partial C_a}{\partial P_{G1}} = 7.92 + 0.003124P_{G1} - \lambda = 0$$

$$\frac{\partial C_a}{\partial P_{G2}} = 7.85 + 0.00388P_{G2} - \lambda = 0$$

$$\frac{\partial C_a}{\partial P_{G3}} = 7.97 + 0.009644P_{G3} - \lambda = 0$$

$$\frac{\partial C_a}{\partial \lambda} = P_{G1} + P_{G2} + P_{G3} - 850 = 0$$

Solve 4 condition equations above for 4 variables, the optimal set points are obtained:

$$\begin{aligned}\lambda^* &= 9.1483 \\ P_{G1}^* &= 393.1936 \\ P_{G2}^* &= 334.6229 \\ P_{G3}^* &= 112.1834\end{aligned}$$

The solution can be described visually in figure 7. Obtain from the first 3 equations of necessary conditions, P_{Gi} can be written as functions of λ. When P_D is given, the economic incremental cost $\lambda^*$of all generators can be calculated from the power balance condition. Because all generators operate at the same incremental cost, each generator can use λ^* as an index to look up the associated generating power from the chart obtained in figure 6.

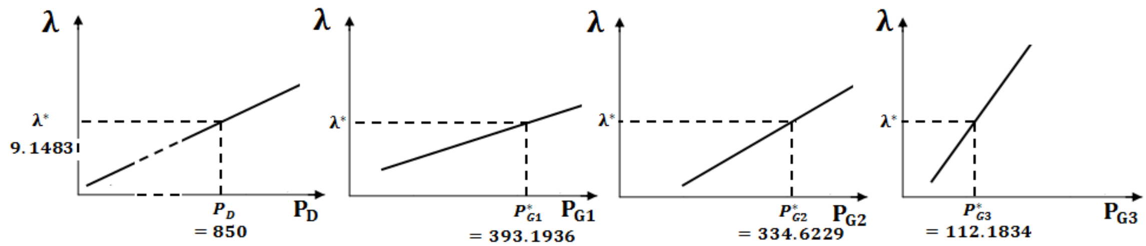

Figure 7: Finding economic set points using Lagrange multiplier

3.3.2 Economic dispatch with transmission losses

In bus bar economic dispatch, all losses are neglected. However, the transmission losses are always there in reality. Let us call the power losses on the transmission line is P_L, then the power balance condition in (3.3) has to take it into account:

$$\emptyset = \sum_{i=1}^{N} P_{Gi} - P_D - P_L = 0 \tag{3.10}$$

Because the losses depend on the power of each generator, let we assume that P_L is a known function of P_{Gi}: $P_L = P_L(P_{Gi})$. The Lagrange function (3.5) now becomes:

$$\min_{P_{Gi},\lambda} C_a = \sum_{i=1}^{N}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) - \lambda\left(\sum_{i=1}^{N} P_{Gi} - P_D - P_L\right) \tag{3.11}$$

The necessary conditions for C_a to have a minimum value are:

$$\frac{\partial C_a}{\partial P_{Gi}} = \frac{dC_i}{dP_{Gi}} - \lambda + \lambda\frac{\partial P_L}{\partial P_{Gi}} = 0 \tag{3.12}$$

$$\sum_{i=1}^{N} P_{Gi} - P_D - P_L = 0 \tag{3.13}$$

The condition (3.12) can be rewritten as:

$$IC_i = \lambda\left(1 - \frac{\partial P_L}{\partial P_{Gi}}\right) \Longrightarrow L_i IC_i = \lambda \tag{3.14}$$

Where:

$$IC_i = \frac{dC_i}{dP_{Gi}} \tag{3.15}$$

$$L_i = \frac{1}{1 - \frac{\partial P_L}{\partial P_{Gi}}} = \frac{1}{\alpha_i} \tag{3.16}$$

L_i is called penalty factor. If L_i =1 $\Longrightarrow \frac{\partial P_L}{\partial P_{Gi}} = 0$, which means the losses does not change when more power is generated from unit i. As L_i increases, the losses will also increase.

In order to find the optimal solution for (3.11), the losses P_L needs to be found from the initial guess of P_{Gi} (could be obtained from bus bar ED). From equation (3.13), P_L can be expressed as:

$$P_L = \sum_{i=1}^{N} (P_{Gi} - P_{Di}) = \sum_{i=1}^{N} f_{Pi} \tag{3.17}$$

with f_{Pi} is the load flow equation:

$$f_{Pi} = P_{Gi} - P_{Di} = V_i^2 G_{ii} + \sum_{\substack{k=1 \\ k \neq i}}^{N} V_i V_k [G_{ik} \cos(\delta_i - \delta_k) + B_{ik} \sin(\delta_i - \delta_k)] \tag{3.18}$$

Where:

G, B: matrices obtained from the admittance matrix $Y_{BUS} = G + jB$

V_i: voltage at bus i

δ_i: phase angle at bus i.

Solving the load flow equation using Jacobian matrix and Newton-Raphson method found in [12] for bus voltages and angles, then plug back into (3.17) and (3.18) to find the losses. When the losses are found, the next step is to compute the penalty factor L_i from the last iteration Jacobian matrix ***J*** in the load flow problem above.

$$\begin{bmatrix} \frac{\partial f_{P2}}{\partial \delta_2} & \frac{\partial f_{P3}}{\partial \delta_2} & \cdots & \frac{\partial f_{PN}}{\partial \delta_2} \\ \frac{\partial f_{P2}}{\partial \delta_3} & \frac{\partial f_{P3}}{\partial \delta_3} & \cdots & \frac{\partial f_{PN}}{\partial \delta_3} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_{P2}}{\partial \delta_N} & \frac{\partial f_{P3}}{\partial \delta_N} & \cdots & \frac{\partial f_{PN}}{\partial \delta_N} \end{bmatrix} \begin{bmatrix} 1-\frac{\partial P_L}{\partial P_{G2}} \\ 1-\frac{\partial P_L}{\partial P_{G3}} \\ \vdots \\ 1-\frac{\partial P_L}{\partial P_{GN}} \end{bmatrix} = \begin{bmatrix} -\frac{\partial f_{P1}}{\partial \delta_2} \\ -\frac{\partial f_{P1}}{\partial \delta_3} \\ \vdots \\ -\frac{\partial f_{P1}}{\partial \delta_N} \end{bmatrix}$$
$$\Leftrightarrow \quad \boldsymbol{J^T} \quad * \quad \boldsymbol{\alpha} \quad = \quad \boldsymbol{b} \tag{3.19}$$

Where:

J^T: transpose of the last iteration Jacobian matrix obtained in load flow problem

α: the unknown vector in (3.16) which is needed to calculate the penalty factors.

b: can also be obtained from the solution of the slack bus in load flow problem

Find **α** from the results of load flow problem, then we can calculate the penalty factor using the equation in (3.16), and the incremental cost considering losses L_iIC_i of each generator using equation (3.14). Because at the economic set points, all the generators operate at the same cost **λ**, so if all the L_iIC_i are not equal, then we have to adjust the power of the generators and solve the whole process again until the solution is found.

The calculation of economic dispatch considering transmission losses can be shown in the flow chart below:

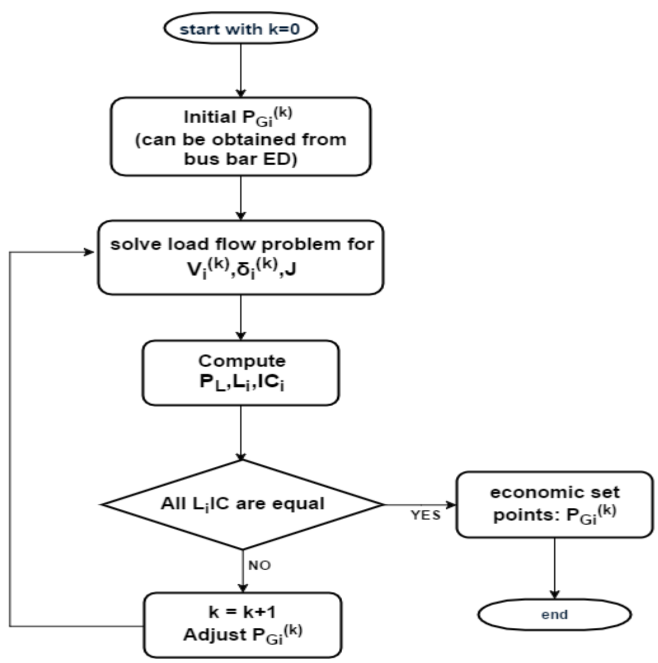

Figure 8: Economic dispatch with losses

Chapter 4

Kalman Filter for PV power Prediction

4.1 State-space model of solar irradiance and temperature

Solar irradiance and temperature are two variables that need to be specified in order to calculate the power of a PV generator. By predicting their values, we can easily have the prediction of the output of a PV plant.

Let us consider a very simple system in which solar irradiance and temperature are only 2 state variables:

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} Irr \\ Temp \end{bmatrix} \tag{4.1}$$

The model should be able to express the temporal relationship between the current values of solar irradiance, temperature and their future values at the next fixed time period ahead. The value of the next state *k+1* is simply the value at the current state *k* plus the rate of change of the variables between the states.

$$x^{k+1} = x^k + \Delta x^{k+1} \tag{4.2}$$

The rate of change Δx^{k+1} is the nature change of the weather in irradiance and temperature between time period *k* and *k+1*. Figure 9 illustrates the irradiance change from period *k* (at 8:00AM) to period *k+1*(at 8:15AM). Between this time of a day, there is a logical guess that the sun is rising and the amount of irradiance is following an increasing "trend" which is u_1^{k+1}. This u_1^{k+1} can be seen as the best estimate input of the system that will drives x^k to x^{k+1} . However, there are too many factors that could make the change deviate from this trend, and therefore we assume this deviation is more likely to vary around the trend within the variance Q_1. From this observation, the rate of change can be split into 2 parts.

$$\Delta x^{k+1} = u^{k+1} + \omega^{k+1} \tag{4.3}$$

Where:

u^{k+1}: the input trend of the change between time period k and $k+1$

$\omega^{k+1} \sim N(0, Q^{k+1})$: the uncertainty of the change from k to $k+1$.

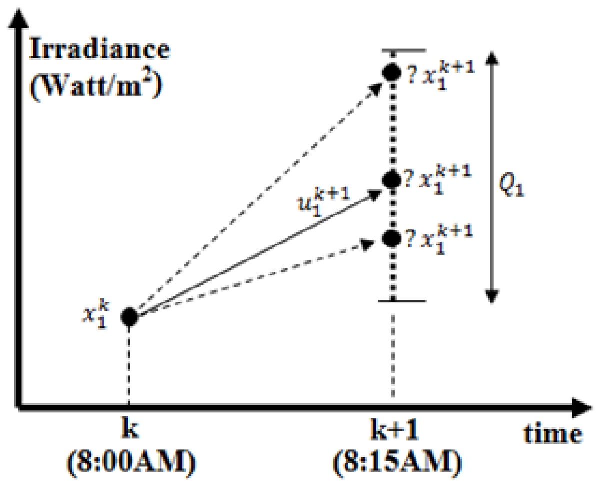

Figure 9: The change in solar irradiance with trend and uncertainty

The discrete time-invariant model for solar irradiance and temperature then can be expressed as follows:

$$\begin{aligned} x_1^{k+1} &= x_1^k + u_1^{k+1} + \omega_1^{k+1} \\ x_2^{k+1} &= x_2^k + u_2^{k+1} + \omega_2^{k+1} \\ \Leftrightarrow \begin{bmatrix} x_1^{k+1} \\ x_2^{k+1} \end{bmatrix} &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1^k \\ x_2^k \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u_1^{k+1} \\ u_2^{k+1} \end{bmatrix} + \begin{bmatrix} \omega_1^{k+1} \\ \omega_2^{k+1} \end{bmatrix} \\ \Rightarrow x^{k+1} &= Fx^k + Bu^{k+1} + \omega^{k+1} \end{aligned} \tag{4.4}$$

Where $\omega \sim N(0, Q^k)$ is the Gaussian distributed uncertainty with mean 0 and the covariance matrix Q^k of u_1^k and u_2^k which are assumed to be uncorrelated.

$$Q^k = \begin{bmatrix} Q_1^k & 0 \\ 0 & Q_2^k \end{bmatrix} \tag{4.5}$$

The outputs of this system are the irradiance and temperature which are also the state variables of the system.

$$\begin{bmatrix} y_1^k \\ y_2^k \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1^k \\ x_2^k \end{bmatrix}$$
$$\Longrightarrow y^k \;=\; Hx^k \tag{4.6}$$

4.2 Solar irradiance and temperature prediction using Kalman Filter

4.2.1 State prediction based on state-space model.

At a certain time k, we do not know the exact values of x^k. There are a whole range of possible values and some of them might be closer to the actual one than the others. Let us call the best state estimate at time k is $\boldsymbol{\hat{x}^k}$ (the mean of the Gaussian blob of its covariance matrix $\mathbf{P^k}$).

$$\hat{x}^k = \begin{bmatrix} \hat{x}_1^k \\ \hat{x}_2^k \end{bmatrix} \tag{4.7}$$

$$P^k = \begin{bmatrix} \Sigma_{Irr} & 0 \\ 0 & \Sigma_{Temp} \end{bmatrix} \tag{4.8}$$

The estimate $\hat{x}^k$ and covariance matrix P^k represent a region that more likely contains the actual values of the system states. The whole region of state estimation is shown in figure 10, and the mean is chosen to be the best estimate.

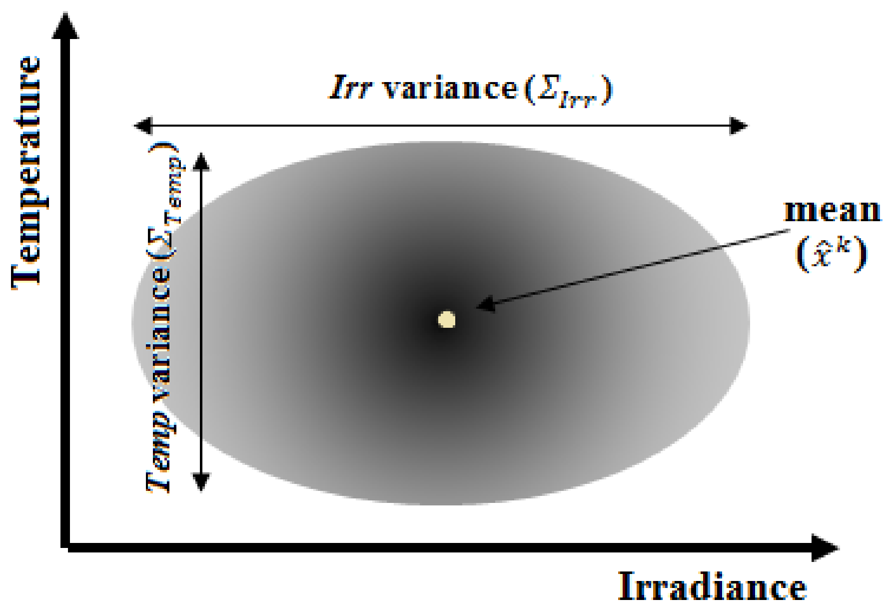

Figure 10: Gaussian distributed of irradiance and temperature variables

Let us call the notations:

$\hat{\boldsymbol{x}}_{\boldsymbol{k|k}}$: the state estimate at current time *k* given the measurement at time *k*

$\hat{\boldsymbol{x}}_{\boldsymbol{k+1|k}}$: the state prediction for next time *k+1* given the measurement up to current time *k*

At this moment we already have the state estimate at current time $\hat{\boldsymbol{x}}_{\boldsymbol{k|k}}$ and the covariance matrix $\boldsymbol{P}_{\boldsymbol{k|k}}$. The next step is to predict the states at time *k+1* using equation (4.4)

$$\begin{aligned} \hat{x}_{k+1|k} &= F\hat{x}_{k|k} + Bu_{k+1|k} \\ &= \hat{x}_{k|k} + u_{k+1|k} \end{aligned} \tag{4.9}$$

Because of the Gaussian distributed uncertainty ω^{k+1}, the covariance matrix at time *k+1* also needs to be updated according to [13]:

$$\begin{aligned} P_{k+1|k} &= FP_{k|k}F^T + Q^{k+1} \\ &= P_{k|k} + Q^{k+1} \end{aligned} \tag{4.10}$$

This whole predicting process can be explained in figure 11. Every single point in the estimated region of time *k* is transformed into a new predicted point at time *k+1*. However, due to the uncertainty ω^{k+1} in equation (4.4), a new predicted point may vary around in a region with covariance Q^{k+1}. Thus, the predicted region of the system states will be enlarged.

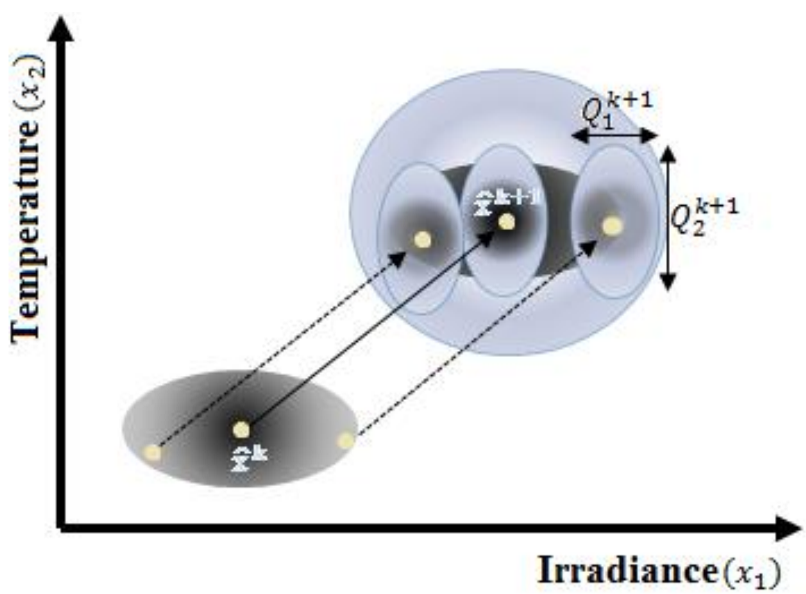

Figure 11: Kalman Filter - Prediction Step

4.2.2 Refining predicted states with sensor measurements.

In the work of this thesis, each PV plant is assumed to have a sensor network that captures solar irradiance and temperature values in the PV field.

At time *k*, we have predicted the states at time *k+1* is a Gaussian blob with mean $\hat{x}_{k+1|k}$ and covariance $P_{k+1|k}$. With this prediction, the expected outputs (or measurements) at time *k+1* can be obtained from equation (4.6).

$$\begin{aligned} y^{k+1} &= H\hat{x}_{k+1|k} \\ &= \hat{x}_{k+1|k} \end{aligned} \tag{4.11}$$

y^{k+1} is the best prediction we have for the outputs at time *k+1* with all the information we have up to time *k*.

When the system is at time *k+1*, we now have access to the measurements of the system outputs from the sensors and call it $\boldsymbol{z^{k+1}}$. Because sensors also have noise, the actual outputs might not be $\boldsymbol{z^{k+1}}$ but vary around it with covariance $\boldsymbol{R^{k+1}}$.

$$z^{k+1} = \begin{bmatrix} z_1^{k+1} \\ z_2^{k+1} \end{bmatrix} \tag{4.12}$$

$$R^{k+1} = \begin{bmatrix} R_1^{k+1} & 0 \\ 0 & R_2^{k+1} \end{bmatrix} \tag{4.13}$$

So, at this time *k+1*, we have 2 different Gaussian blobs of the system outputs (see fig.12), which are:

- The expected measurement with mean y^{k+1} and covariance $P_{k+1|k}$
- the sensor measurement with mean $\boldsymbol{z^{k+1}}$ and covariance R^{k+1}

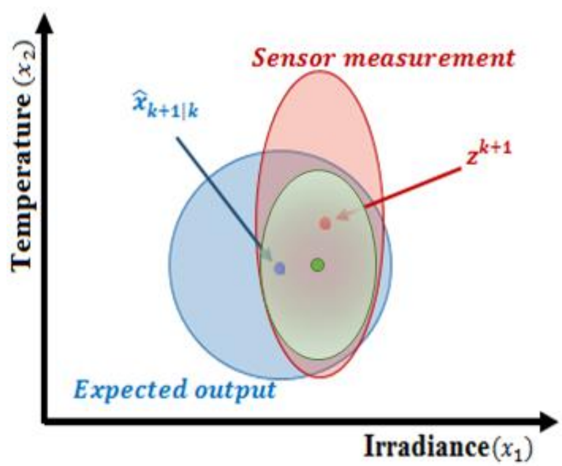

Figure 12: Prediction and sensor measurement Gaussian blobs

To refine the estimate at time *k+1*, Kalman Filter combines these two Gaussian blobs by taking their product which is also a new Gaussian blob. This new Gaussian blob has its mean chosen to be the best estimate ($\hat{x}_{k+1|k+1}$) at time *k+1*, and its covariance is $P_{k+1|k+1}$

The mean and covariance of this new Gaussian blob are calculated using Kalman gain matrix K^{k+1}. The derivation of Kalman gain matrix can be found in [14].

$$\begin{aligned} K^{k+1} &= P_{k+1|k}H^T\left(HP_{k+1|k}H^T + R^{k+1}\right)^{-1} \\ &= P_{k+1|k}\left(P_{k+1|k} + R^{k+1}\right)^{-1} \end{aligned} \tag{4.14}$$

With this Kalman gain matrix K^{k+1}, the best estimate at time *k+1* and its covariance can be found as follows:

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K^{k+1}(z^{k+1} - \hat{x}_{k+1|k}) \tag{4.15}$$

$$P_{k+1|k+1} = P_{k+1|k} - K^{k+1}P_{k+1|k} \tag{4.16}$$

At this point, the time has shifted from k to k+1, the next step is to update the timeline and start the whole process again at *k+1* (see figure 12).

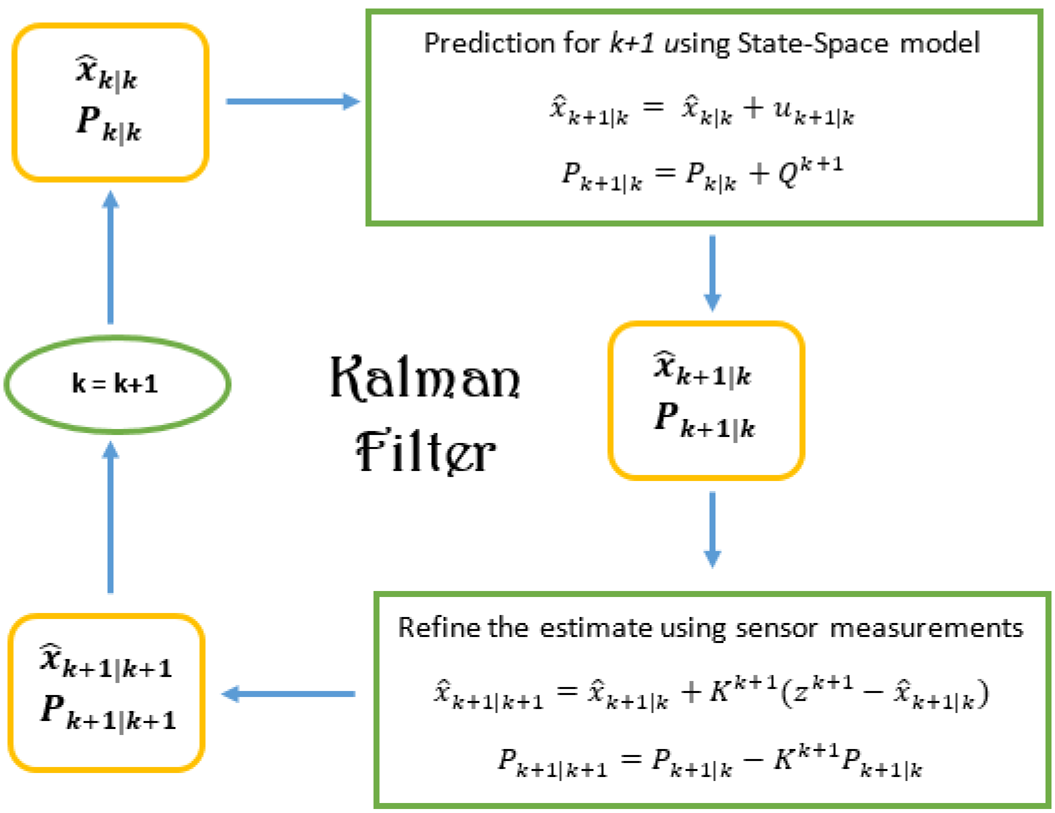

Figure 13: Kalman filter process

4.3 The prediction of system input.

From equation (4.9) we can observe that the Kalman filter prediction for the system state at *k+1* relies on the input $u_{k+1|k}$, and as described in 4.1, this input is based on an initial guess that somehow follow a trend at a specific time in a day (could be a logical guess as in 4.1 or from local weather forecast...).

Because of the weather changes are naturally slow in a short-time period, the predicted input could be more accurate if it combines the information from the direct previous input and the initial guess.

$\boldsymbol{u_{k+1|k}}$ is our predicted input at time *k+1* using previous input $u_{k|k}$ at time *k*, and the initial guess u_{Init}^{k+1} at time *k+1*. The simple moving average method [15] is chosen to predict $u_{k+1|k}$ because of its simplicity and effectiveness in short-term prediction.

$$u_{k+1|k} = (u_{Init}^{k+1} + u_{k|k})/2 \tag{4.17}$$

Where $u_{k|k}$ can be extracted from (4.9) at time *k*.

$$u_{k|k} = \hat{x}_{k|k} - \hat{x}_{k-1|k-1} \tag{4.18}$$

4.4 Persistent forecasting model

The persistent forecasting model (PSS) assumes that the values of solar irradiance and temperature in the next time period is the same as the previous one.

$$y^{k+1} = y^k \tag{4.19}$$

In other word, the PSS model assumes that the future prediction equals to the current measured data. From equation (4.19), the issues of this model are the delay between the forecast time and the observation. This delay is illustrated in figure 14.

For short-term forecasting, due to the slow change of weather, PSS works very well. If a forecasting model can outperform PSS, that model is considered to be good.

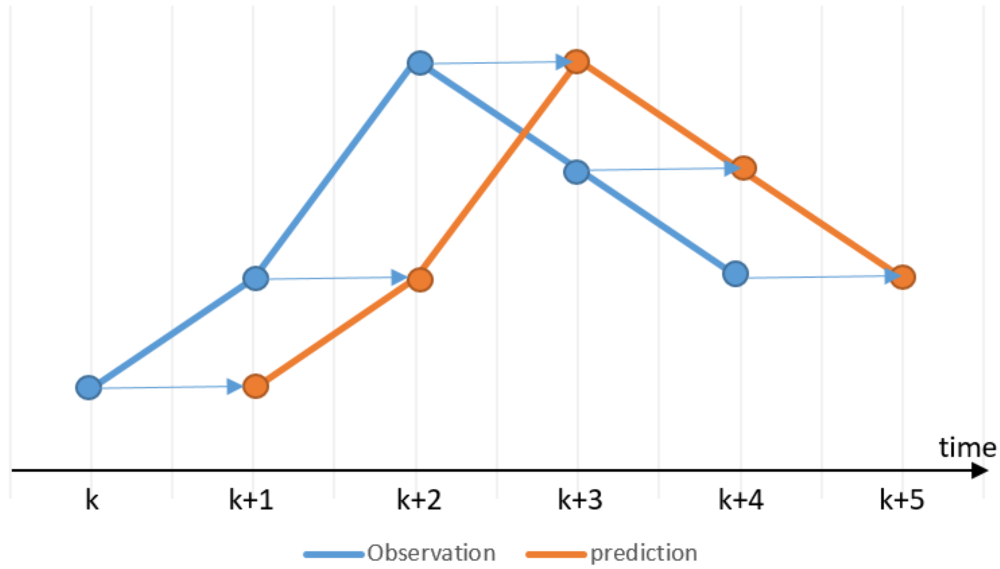

Figure 14: Persistent Forecasting Model

4.5 PV power calculation based on irradiance and temperature

Once the values of solar irradiance and temperature are specified, the next step is to compute the power that a PV plant can generate associated with those values. The methodology for PV power calculation is given in [16]. The final formula to compute PV power output of a PV array is as follows:

$$P_G = P_R f_P \left(\frac{Irr}{Irr_{STC}}\right)[1 + \alpha_P(Temp - Temp_{STC})] \tag{4.20}$$

Where:

P_G: output of the PV array (W)

P_R: rated output of the PV array under standard test condition (W)

f_P: derating factor (efficiency factor) (%)

Irr: solar irradiance striking the PV array (W/m^2)

Irr_{STC}: solar irradiance at standard test condition (W/m^2)

$Temp$: PV cell temperature (^{o}C)

$Temp_{STC}$: PV cell temperature at standard test condition (^{o}C)

α_P: temperature coefficient of the power (%/^{o}C)

Chapter 5

Case Study and Results

In this chapter, a Kalman filter for prediction of solar irradiance and temperature as in chapter 4 is implemented. The values are used to calculate the power outputs of 2 PV generators in a test system. These predicted outputs will be used later to solve the bus bar economic dispatch for the system. Information about the test system will also be given at first in this chapter, and the results of Kalman filter prediction as well as the bus bar economic dispatch will be discussed at the end.

5.1 Case study information

5.1.1 IEEE 24-bus reliability test system

The system selected for this thesis is the IEEE 24-bus reliability test system (RTS). It represents the transmission level of power system where the electricity wholesale market takes place with connected generators and loads. The raw data of this system can be found on the website of University of Washington [17]. However, P. Pinson has collected and compiled all the data and make it ready to use as in [18].

The one-line diagram of the system is given in figure 14. In this case study, only the bus bar economic dispatch is used because the objective is to study the effect of renewable energy under uncertainty on economic dispatch problem rather than the security constraints in ED.

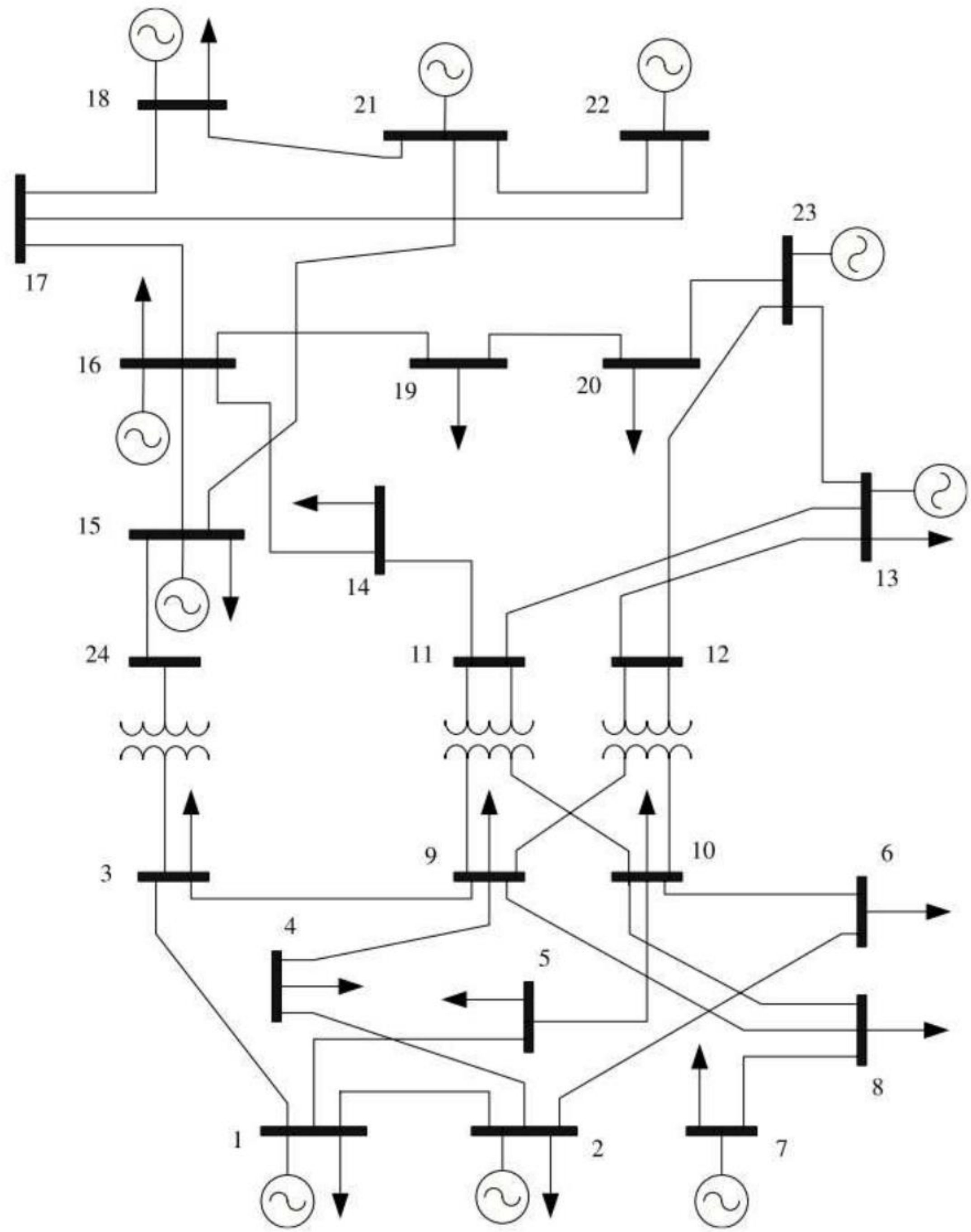

Figure 15: IEEE 24-bus Reliability Test System

The data of generating units is modified from IEEE 24-bus system in order to place 2 PV generators into the system at bus 13 and bus 18. The generator data is given in table 2 including the power constraint obtained in [18] and cost coefficients obtained in [19].

Bus #	Power Constraint		Cost coefficients			Unit Type
	Pmax	Pmin	γ	β	α	
1	252	10	0.6568	56.564	400.6849	Diesel
2	352	30.4	0.00921	13.3939	81.545	Coal/Stream
7	350	75	0.00611	18.1	218.3351	Oil/Stream
13	120	0	0.0004	4.4231	395.3749	PV
15	215	66.25	0.00463	10.1694	142.7348	Coal/Stream
16	155	54.25	0.00473	10.7154	143.0288	Coal/Stream
18	150	0	0.0004	4.4231	395.3749	PV
21	591	206.85	0.00261	23.1	259.652	Nuclear
23	660	248.5	0.00153	10.8616	177.0575	Hydro

Table 2: IEEE 24-bus RTS - generating unit parameters

The PV power plants are at bus 13 and 18. Note that $\mathbf{P_{max}}$ of 2 PV generators in table 2 is their capacity. The maximum power of these 2 generators is different at each time period and will be specified by the predictive model. The diesel generator at bus 1 is a fast response generator that is used as the spinning reserve in case of PV generators do not have sufficient power to supply the load. Obviously, the cost to generate power of that diesel unit is very high.

The total load profile is illustrated in figure 15, and the total system demand per hour is given in table 3.

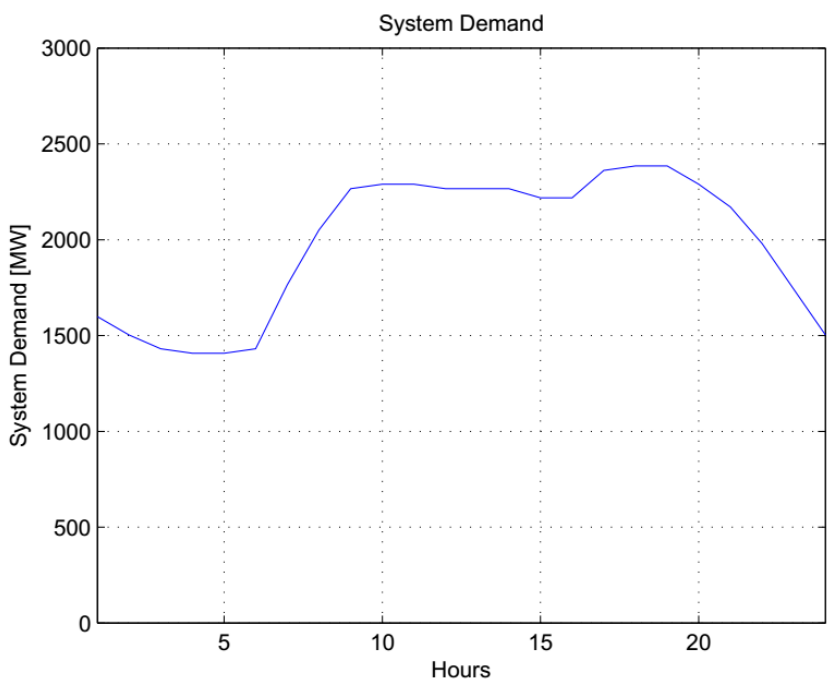

Figure 16: System Demand Profile

hour	Demand (MW)	hour	Demand (MW)
1	1598.252	13	2266.178
2	1502.834	14	2266.178
3	1431.27	15	2218.469
4	1407.416	16	2218.469
5	1407.416	17	2361.596
6	1431.27	18	2385.45
7	1765.233	19	2385.45
8	2051.487	20	2290.032
9	2266.178	21	2170.76
10	2290.032	22	1979.924
11	2290.032	23	1741.379
12	2266.178	24	1502.834

Table 3: System demand profile (per hour)

5.1.2 Solar irradiance and temperature data

The real minute to minute data from National Renewable Energy Laboratory on 03/19/2017 from 6:08AM to 6:07PM is accessible in [20]. This data of irradiance and temperature will be used as the reference for the prediction using the method described in chapter 4.

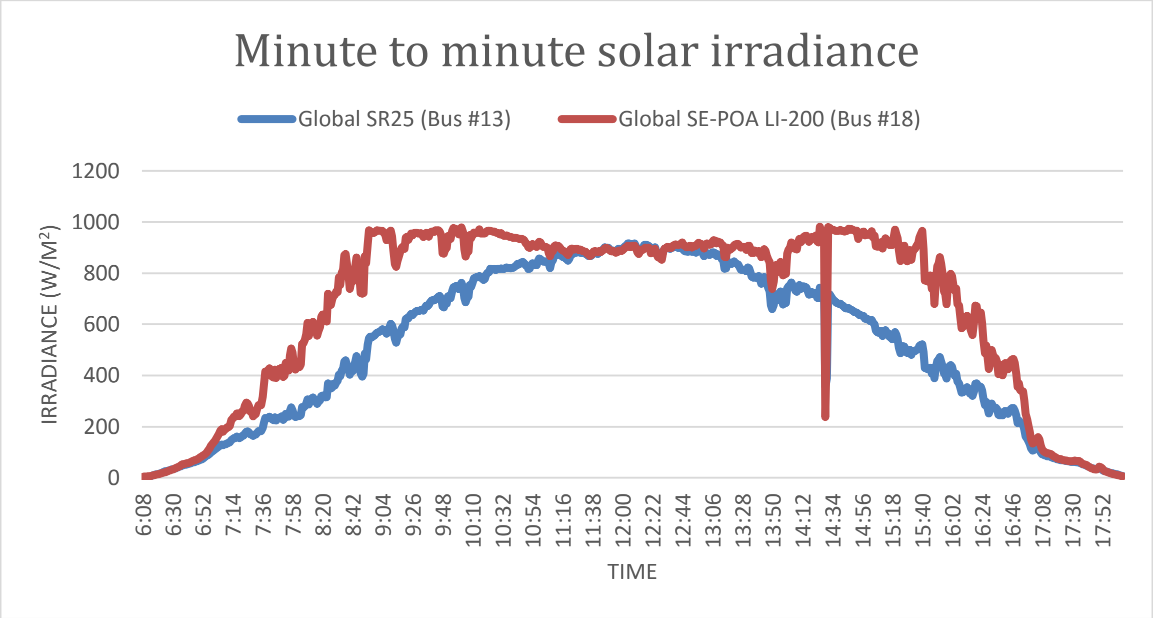

Figure 17: minute to minute solar irradiance data at 2 PV buses

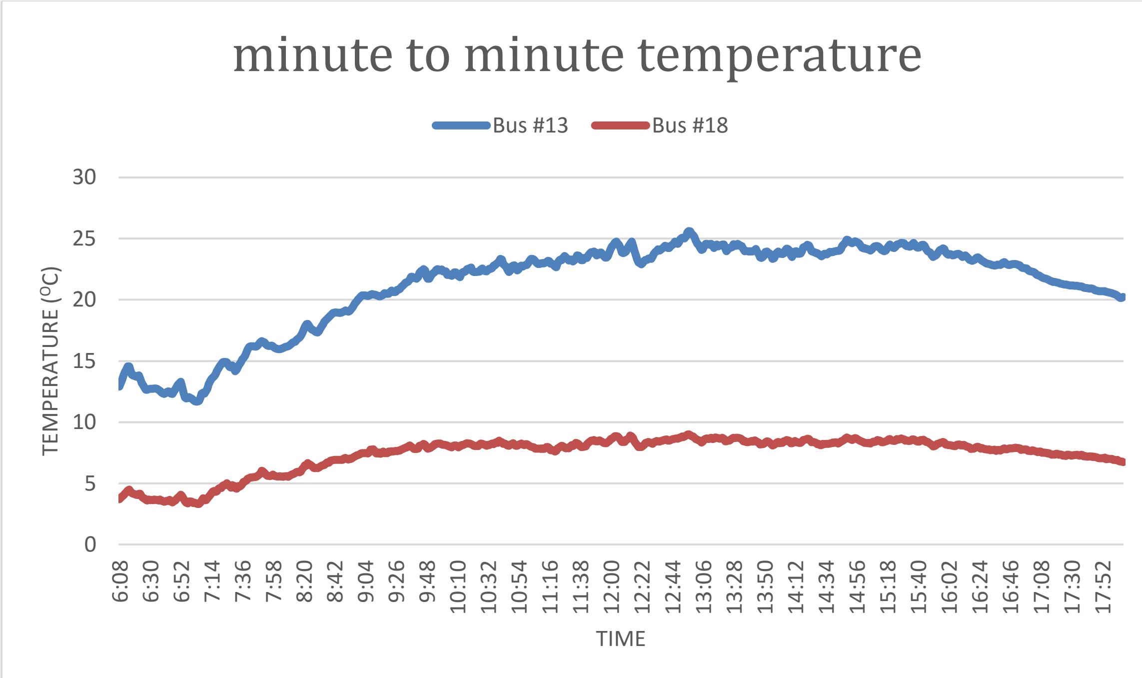

Figure 18: minute to minute temperature data at 2 PV buses

5.1.3 Solar panel specifications of the PV plants

This case study assumes that both PV power plants on bus 13 and 18 are using the same solar panel given in [21]. The specifications of the solar plants needed for the formula (4.19) is in table 4.

	Notation	PV at bus #13	PV at bus #18
Rated power*	P_R	120 MW	150 MW
Irradiance at standard test condition	Irr_{STC}	1000 (W/m^2)	1000(W/m^2)
Temperature at standard test condition	$Temp_{STC}$	25^{o}C	25^{o}C
Temperature coefficients	α_P	-0.38%/^{o}K	-0.38%/^{o}K

Table 4: Specifications of solar panels used in 2 PV plants

* The rated power is the maximum power of PV plants obtained from table 2, it can be change to study the effect of different PV power penetration to the system.

5.2 Implementation of the proposed prediction method

The prediction method introduced in chapter 4 is implemented using MATLAB. Start from period *k=0* at 6:08AM, the prediction will be done for only one step ahead at time *k=1* (6:23AM) with 15-minute period (time period can be change). At 6:23AM, the data in figure 16 and 17 is used as the actual data of irradiance and temperature. By adding the sensor noise *R* into this data at this time, we will obtain the sensor measurement and feed it to the Kalman filter to refine the state estimate at time *k=1*. The process now is already at *k=1*, the prediction is again being done for *k=2* and one step by one step ahead until we get to the end of the reference data at 6:17 PM. The visual explanation for this process can be seen in figure 18.

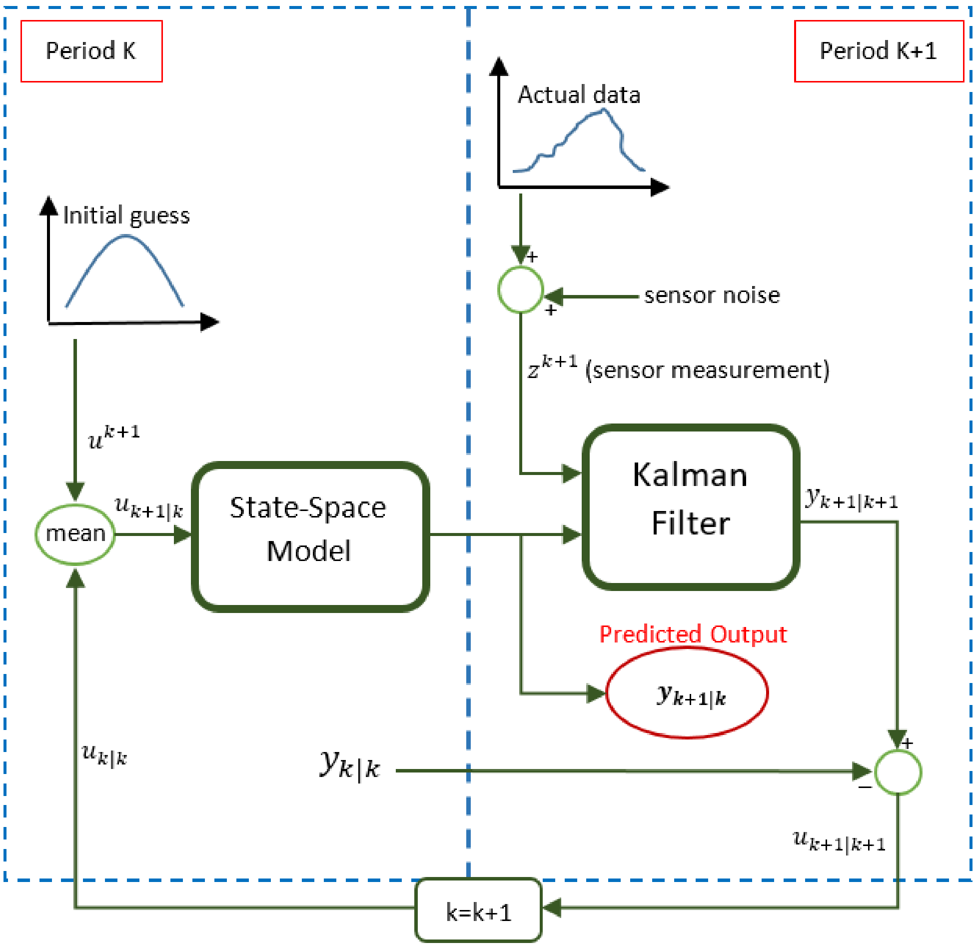

Figure 19: The whole predicting model

The results of this prediction will be compared with the results of persistent forecasting method PSS. If this predicting model can outperform PSS, it is considered to be good.

5.2.1 The choice of initial guess

As described in chapter 4, the initial guess is used as the trend to predict the output using state-space model before the output is refined by Kalman filter. If the trend is close to the actual output, then the Gaussian blob of the estimated output after the Kalman filter will be smaller which results in better estimate for the next prediction.

The initial guess can be obtained from the local weather forecast or just from a logical guess such as the Sun is rising in the morning and setting in the afternoon, and temperature is quite persistent from day time. Based on this, the initial guess in this case study for irradiance would be a half sinusoidal waveform starting from 6:08AM and ending at 6:07PM, and the temperature is a persistent line as in figure 19 and 20.

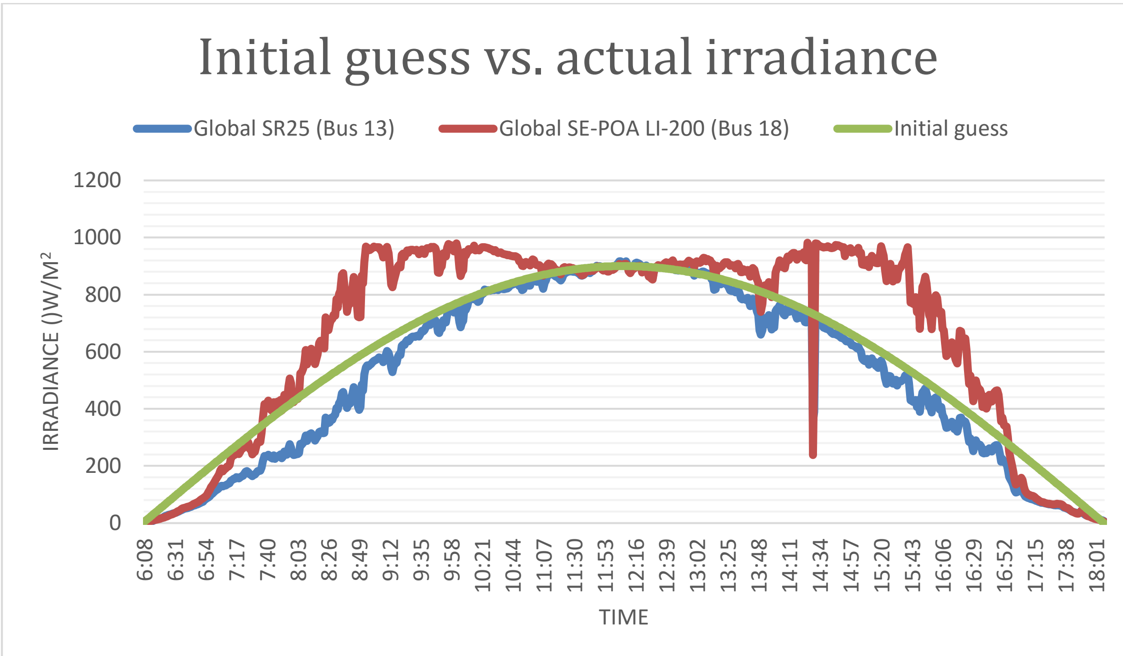

Figure 20: Initial guess of irradiance

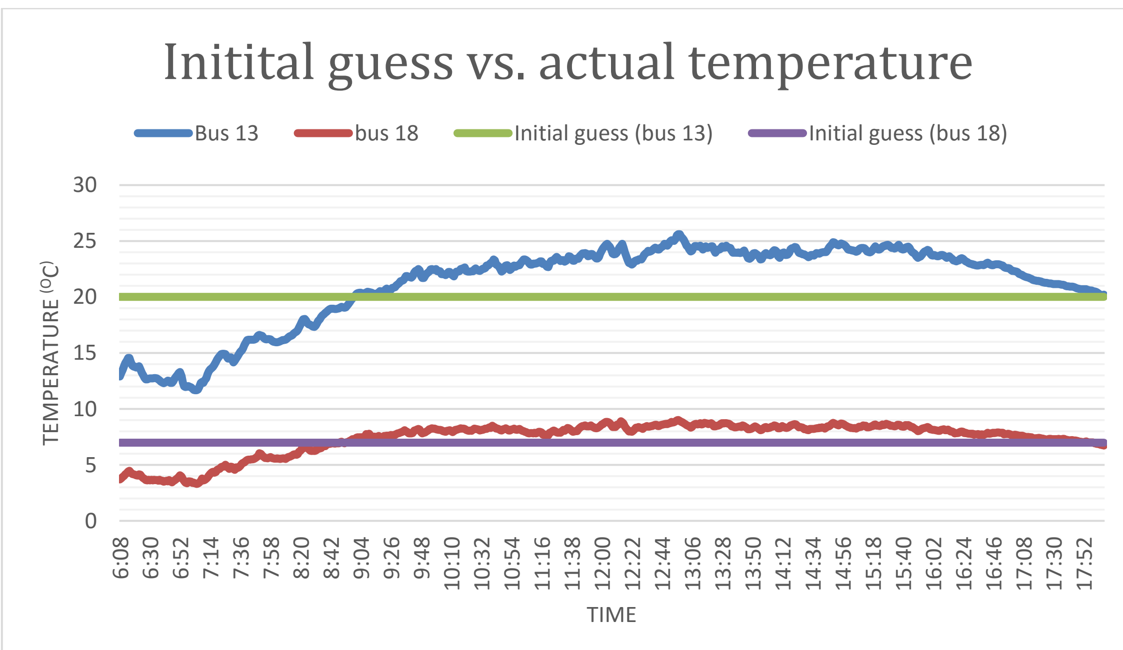

Figure 21: Initial guess of temperature

5.2.2 Results of the predicting model

Everything needed to run the model in figure 18 is available. Running the model with 15-minute time period from 6:08AM to 6:07PM, the predicted outputs of the proposed model, PSS and actual outputs will be shown in the same plots for comparison.

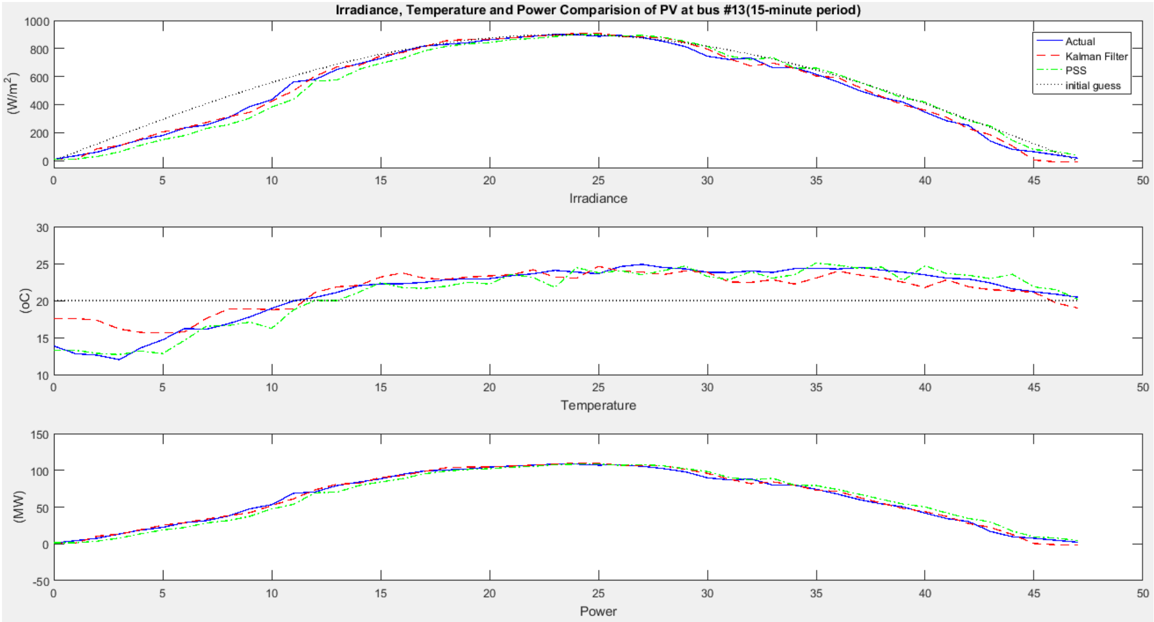

Figure 22: Comparison of irradiance, temperature and power at bus #13

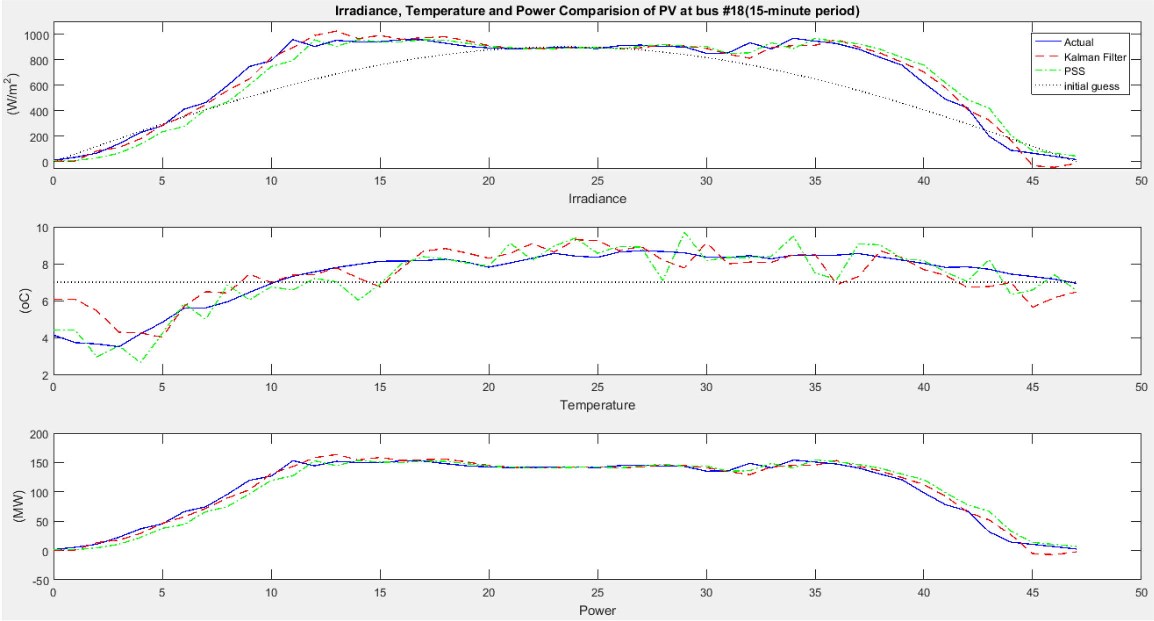

Figure 23: Comparison of irradiance, temperature and power at bus #18

As we can observe from figure 21 and 22 above, the prediction of irradiance and temperature of the model using Kalman filter is closer to the actual values than the PSS model. For easier observation, the deviation of the predicted power from the actual power generated can be seen in figure 23 and 24.

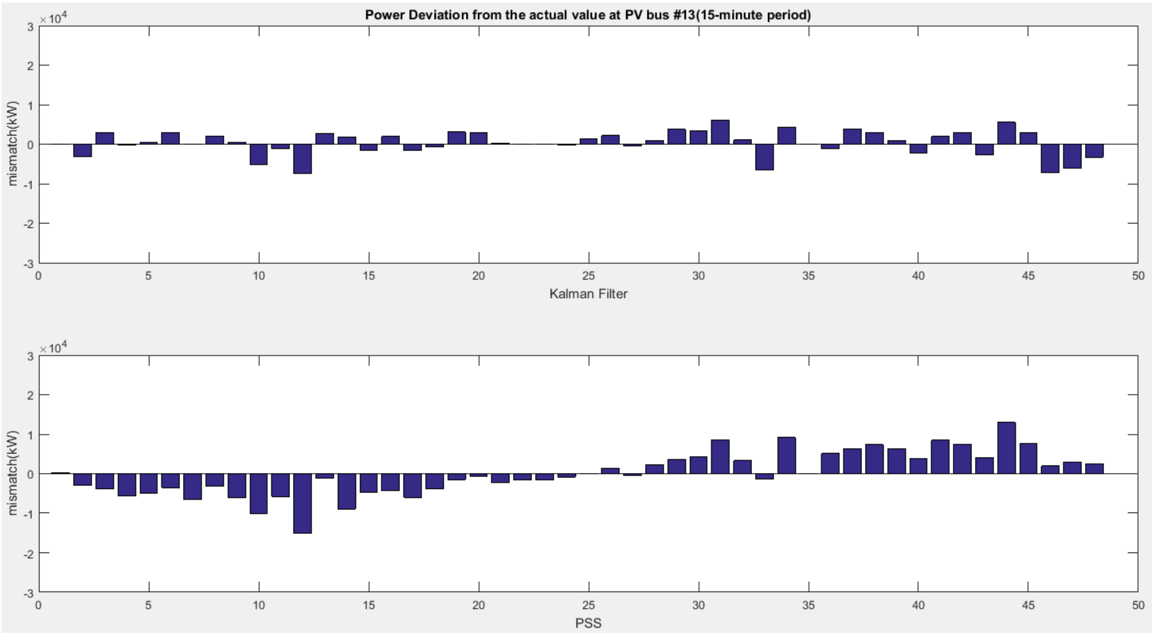

Figure 24: Power deviation from actual value at PV bus #13

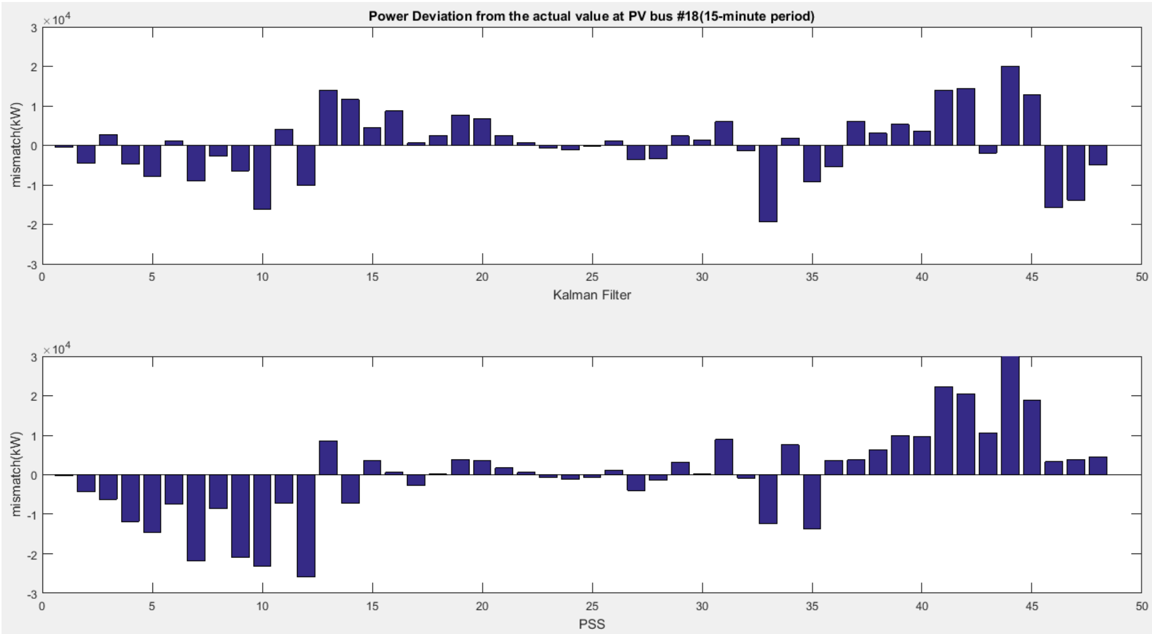

Figure 25: Power deviation from actual value at PV bus #18

It is easily to see that the power mismatch from Kalman filter approach is less than PPS. From this power mismatch, the percentage error of the predicted energy in the whole time t (in hour) can be calculated as:

$$\%E_{err} = \frac{\sum|E_{mismatch}|}{E_{actual}} * 100\% = \frac{\sum|P_{mismatch}| * t}{P_{actual} * t} * 100\%$$

The percentage energy mismatch calculated for Kalman filter approach and PSS using the formula above is given in the tables below:

Bus	**Approach**	$\boldsymbol{E_{actual}}$ (MWh)	$\sum\lvert\boldsymbol{E_{mismatch}}\rvert$ (MWh)	$\%\boldsymbol{E_{err}}$
13	Kalman Filter	746.43	29.36	3.93
	PSS		54.31	7.28
18	Kalman Filter	1,274.38	75.54	5.93
	PSS		98.23	7.71

Table 5: Energy deviation from the actual value

5.3 Bus bar economic dispatch using results of the prediction model

Once the predicted power of the 2 PV plants is available for the next period, the system will run economic dispatch with the new updated for maximum power constraint of those 2 PV generators. Besides, in case of the predicted power of these 2 PV generators is higher than the actual value, the fast response diesel generator as bus 1 will compensate for those power mismatch as a spinning reserve. The cost of this unit is very high.

The cost of economic dispatch under different penetration levels of PV power will be discussed in the next sections. The penetration level is the percentage of actual energy generated from PV generators over total demand energy of the load from 6:08AM to 6:07PM. The demand energy is 25,929.85 MWh and can be calculated from table 3.

5.3.1 Cost of economic dispatch with 8% PV power penetration

With the capacity of 2 PV generators in table 2, the actual energy produced from 6:08AM to 6:07PM of these 2 generators is 2,020.81 MWh which is 7.8% of the total demand.

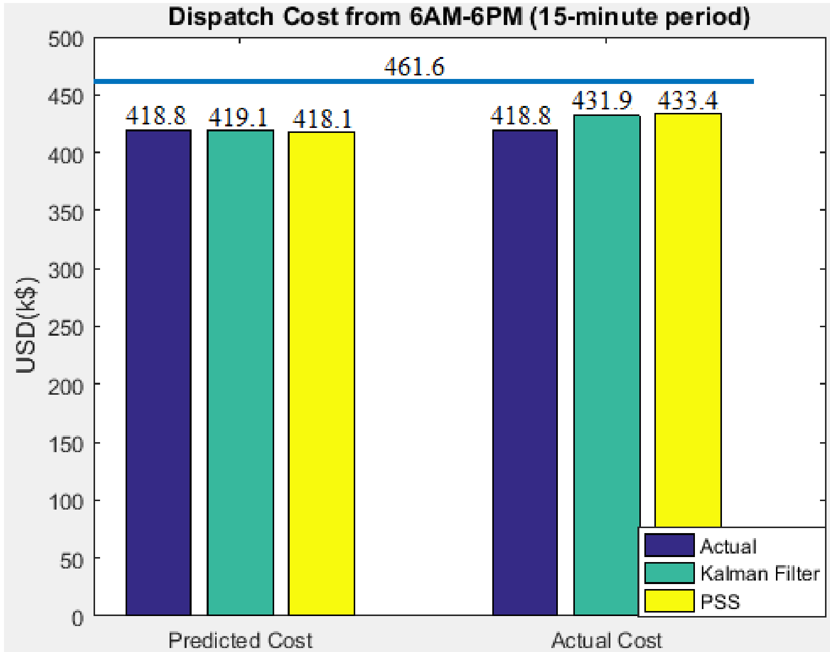

Figure 26: Cost of Economic Dispatch with 8% PV penetration

The predicted cost is the cost when the system runs economic dispatch based on the predicted power of 2 PV generators.

The actual cost is the cost when the system is following the predicted dispatch schedule at real-time but have to change because the prediction is different from reality.

The line on figure 26 is the cost when the system does not commit PV power.

Approach	Predicted cost (k$)	Actual cost (k$)	Cost Deviation (k$)	Cost deviation (%)
Kalman filter	419.1	431.9	-12.8	-3.06
PSS	418.1	433.4	-15.2	-3.64

Table 6: Dispatch cost deviation with 8% PV penetration

Table 6 above shows that if we run ED using the results from the predictive model base on Kalman filter, then the different between the actual cost and the predicted cost is -12.8 thousand dollars in total from 6:08AM to 6:07PM. Compare to -15.2 thousand dollar deviation cost from PSS model, the Kalman filter approach did a little better with 2.4 thousand dollars less. Remember that the percentage of PV power penetration in this case is just 7.8% of the total load.

5.3.2 Cost of economic dispatch with 19% PV power penetration

By increasing the capacity of 2 PV generators at bus 13 and 18 to 320 MW and 350 MW respectively, the penetration of PV power into the system increase to 19.1%. Doing the same analysis as the section above, we can observe from figure 27 that the Kalman filtering approach still has better performance compare to the PSS approach.

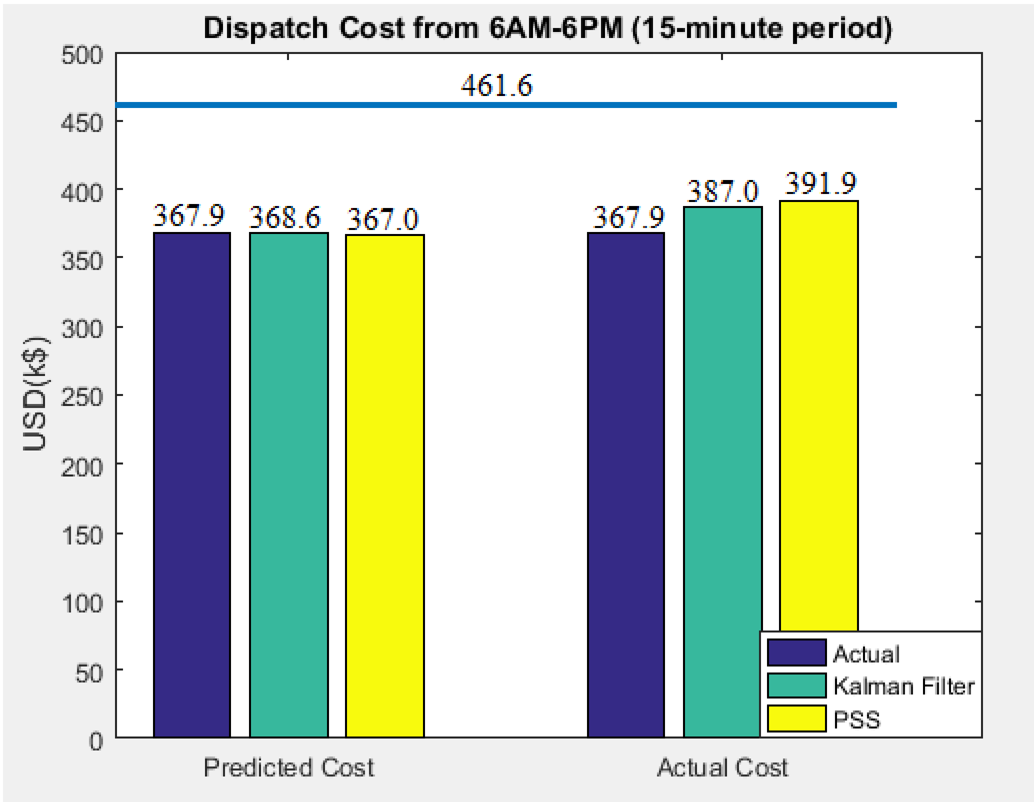

Figure 27: Cost of Economic Dispatch with 19% PV penetration

Table 7 shows that Kalman Filtering approach has 6.5 thousand dollars less than PPS in term of cost deviation between the predicted dispatch cost and actual dispatch cost.

Approach	Predicted cost (k$)	Actual cost (k$)	Cost Deviation (k$)	Cost deviation (%)
Kalman filter	368.6	387.0	-18.4	-5.00
PSS	367.0	391.9	-24.9	-6.78

Table 7: Dispatch cost deviation with 19% PV penetration

5.3.3 Cost of economic dispatch with 42% PV power penetration

The capacity of 2 PV generators in this case is increased up to 720 MW and 750 MW which results in 41.8% of PV power penetration in the system.

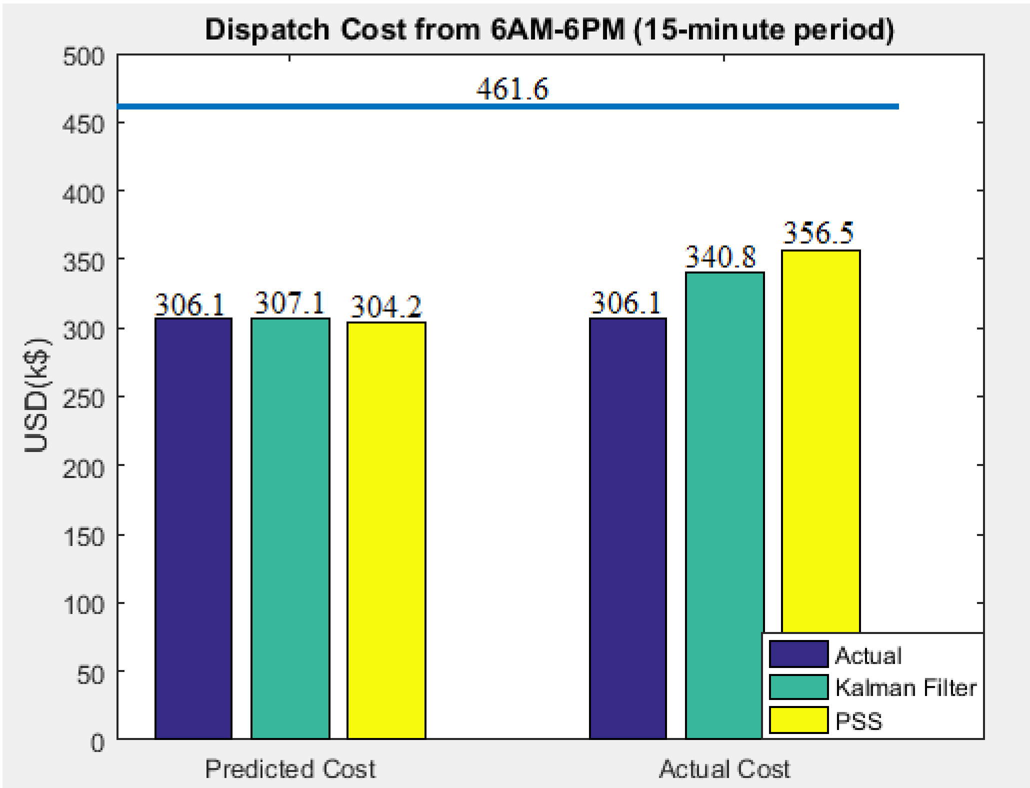

Figure 28: Cost of Economic Dispatch with 42% PV penetration

With this high penetration of PV power, figure 28 and table 8 show that the Kalman filtering approach performs much better with -33.7 thousand dollars or 10.98% of dispatch cost deviation compare to -52.2 thousand dollars or 17.14% of those in PSS approach. This difference would be a significant amount of money if the market is worth millions of dollars.

Approach	Predicted cost (k$)	Actual cost (k$)	Cost Deviation (k$)	Cost deviation (%)
Kalman filter	307.1	340.8	-33.7	-10.98
PSS	304.2	356.5	-52.2	-17.14

Table 8: Dispatch cost deviation with 42% PV penetration

Chapter 6

Conclusion and Future Work

6.1 Thesis conclusion

The work described in this thesis is concerned with the prediction of short-term PV power production for economic dispatch problem. Because of the generation cost of renewable energy such as PV is relatively low, utilizing it will advantage in total production cost of the whole power system. However, the power of this resource cannot be pre-specified but has to be forecasted. Therefore, a good prediction of PV power will obviously help the result of ED problem get close to the optimal solution.

This thesis proposes a prediction model built on Kalman filter for solar irradiance and temperature. The prediction of PV power can be calculated form these 2 variables. First, the prediction starts with an initial guess of irradiance and temperature at each time period. Then, the Kalman filter will refine the results when sensor measurements are updated so that they can be used for better prediction in the next period. The result of the prediction gets better when the initial guess is closer to the actual values. The proposed model is implemented on 2 PV generators of the IEEE 24-bus reliability test system. The real irradiance and temperature data from National Renewable Energy Laboratory is used as the actual outputs that the outputs of the predictive model should get close to.

The simulation is run with different levels of PV penetration. The results of the proposed model are compared with the results from PSS model. It is shown that the proposed model has better performance than the PSS model when its predictive PV power is closer to the actual one and the actual dispatch cost is less than that of the PSS model.

6.2 Future work

Better prediction method will help PV power being more reliable for the power system. The more renewable energy like PV is utilized, the less traditional energy from fossil fuel is used. This will benefit to the environment, and definitely save a lot of money since PV power is cost-effective.

The work in this thesis can be further improved by:

- Beside irradiance and temperature, the model can include more variables that can affect the PV power such as cloud shape, wind speed, wind direction…, find the relationship between these variables so that the model can be more precise.
- Apply the technique to the unit commitment problem when the economic dispatch is done 24 hours ahead for day-ahead market.
- The economic dispatch for the test system can be improved by consider losses as well as other constraints of the generators.
- The same model can be applied for wind power.

Appendix

Matlab program for PV power prediction and Economic dispatch.

Under is the code for Economic Dispatch calculation, it uses the PV power prediction from `Power_Estimation` function where the predictive model using Kalman Filtering approach is implemented.

```
clc;
clear;
system_load = xlsread('SystemLoad24h',1,'B8:B20');%system load from 6AM-6PM
gen_data = xlsread('gen_para',1);% read generators data

%--------------------------------------------------------------------------
% Definitions and data collection
%--------------------------------------------------------------------------
PMAX = 2;
PMIN = 3;
GAMA = 4;
BETA = 5;
ALPHA = 6;
alpha = gen_data(:,ALPHA);
beta = gen_data(:,BETA);
gama = gen_data(:,GAMA);
no_PVs = 2; % Number of PV generators: 2
PVs_bus = [13 18]; % Bus of PV generator: 13 & 18
e = 10^-3; % Economic dispatch error

%--------------------------------------------------------------------------
%Time period
%--------------------------------------------------------------------------
Period_10min = 10;
Period_15min = 15;
Period_30min = 30;
T = Period_15min; %time period in minutes

%--------------------------------------------------------------------------
%Get estimated PV power of 2 PV generators from Kalman Filtering model
%--------------------------------------------------------------------------
[ Preal, Pkal, Ppss ] = Power_Estimation( T, PVs_bus );
Pnopv = zeros(size(Preal));%for system that does not use power from PV

%--------------------------------------------------------------------------
%Bus Bar Economic Dispatch Calculation
%--------------------------------------------------------------------------
%
% IC1 = 2*gama1*PG1 +            0 +  beta1 = lambda
% IC2 =            0 +  2*gama2*PG2 +  beta2 = lambda
%                PG1 +          PG2 +      0 = PD
% <=>
%
% |2*gama1     0     -1|    |   PG1 |    |-beta1|
% |   0     2*gama2  -1| *  |   PG2 | =  |-beta2|
% |   1        1      0|    |lambda|    |   PD   |
```

```
%
% <=>
%            A           *     x     =    B
%---------------------------------------------------------------------------
num_of_T = size(Pkal,1); % Number of periods
Estimated_Cost = zeros(3,1);
Real_Cost = zeros(3,1);
% The estimated dispatch cost based on PV power prediction
for l=1:4
    if l==1
        Ppv = Preal;
    elseif l==2
        Ppv = Pkal;
    elseif l==3
        Ppv = Ppss;
    else
        Ppv = Pnopv;
    end
    Cost = zeros(num_of_T,1);% vector cost of the whole time
    Total_load=0;
    for k=1:num_of_T
        % update Pmax of PV generator at this time period
        [~,genid] = intersect(gen_data,PVs_bus);
        gen_data(genid,PMAX) = Ppv(k,1:no_PVs)/(1e6);%only 2 PVs for now
        gen_data(genid,PMIN) = 0;
        Pmax = gen_data(:,PMAX);
        Pmin = gen_data(:,PMIN);
        PD = system_load(floor(k*T/60)+1);% update PD at that time period
        Total_load = Total_load+PD;
        %setup the max and min of the incremental cost lambda
        lambda_max = max(2*gama.*Pmax + beta);
        lambda_min = min(2*gama.*Pmin + beta);
        %calculate PG with initiate lambda is in the middle
        lambda = (lambda_max + lambda_min)/2;
        PG = (lambda-beta)./(gama*2);
        %check for power constraint with this new lambda
        PG = min(PG,Pmax);
        PG = max(PG,Pmin);
        mismatch = sum(PG) - PD;
        num_of_iteration =0;
        while abs(mismatch) > e
            if mismatch < 0 %not enough Power -> search upper region
                lambda_min = lambda;
            else %too much power -> search lower region
                lambda_max = lambda;
            end
            % adjust lambda, recalculate PG
            lambda = (lambda_max + lambda_min)/2;
            PG = (lambda-beta)./(gama*2);
            %check for power constraint with this new lambda
            PG = min(PG,Pmax);
            PG = max(PG,Pmin);
            mismatch = sum(PG)- PD;% calculate mismatch
            num_of_iteration = num_of_iteration + 1;
        end
        Cost(k) = sum(alpha + beta.*PG + gama.*PG.*PG)*T/60;
    end

    if l==4
        Cost_without_PV = sum(Cost);
    else
        Estimated_Cost(l) = sum(Cost);
    end
```

```
end

%Actual power dispatch
Real_Cost(1) = Estimated_Cost(1);

%Actual dispatch cost for PV power prediction using Kalman approach
Pkalh = max((Pkal - Preal)/(1e6),zeros(size(Pkal)));
Real_Cost(2) = Real_Cost(1) + ...
    sum(sum((alpha(1,:) + beta(1,:).*Pkalh + gama(1,:).*Pkalh.*Pkalh)*T/60));

%Actual dispatch cost for PV power prediction using PSS approach
Ppssh = max((Ppss - Preal)/(1e6),zeros(size(Pkal)));
Real_Cost(3) = Real_Cost(1) + ...
    sum(sum(alpha(1,:) + beta(1,:).*Ppssh + gama(1,:).*Ppssh.*Ppssh)*T/60);

%-------------------------------------------------------------------------
%Plot bar graph the comparison of dispatch costs
%-------------------------------------------------------------------------
figure;
bar([Estimated_Cost'; Real_Cost']/1000),
title(['Dispatch Cost from 6AM-6PM (' num2str(T) '-minute period)']),
ylabel('USD(k$)'),
legend('Actual','Kalman Filter','PSS'),
set(gca,'XTickLabel',{'Predicted Cost','Actual Cost'});
hold on
plot(xlim,[Cost_without_PV Cost_without_PV]/1000,'LineWidth',2)

%-------------------------------------------------------------------------
%Energy deviation, cost deviation and PV power penetration
%-------------------------------------------------------------------------
[sum(abs(Pkal-Preal)) ;sum(abs(Ppss-Preal))];
dEkal = sum(abs(Pkal-Preal))*T/60/1e6%energy deviation (MWh) of Kal appr.
dEpss = sum(abs(Ppss-Preal))*T/60/1e6%energy deviation (MWh) of PSS appr.
Ereal = sum(Preal)*T/60/1e6;%actual energy generated (MWh) from 6AM - 6PM
percent_eng_Kal_deviation = dEkal./Ereal*100
percent_eng_PSS_deviation = dEpss./Ereal*100
Deviation_Cost = Estimated_Cost - Real_Cost % dollar
Percen_Deviation_Cost = Deviation_Cost./Estimated_Cost*100
Percen_PV_Power_Penetration = sum((sum(abs(Preal))/1e6)*100/Total_load)
```

The `Power_Estimation` function is as follows:

```
function [ Preal, Pkal, Ppss ] = Power_Estimation( T, PVs_bus )
% This function estimates the next output of PV power plant using
% Kalman Filter and Persistance Forecasting(PSS)

%-------------------------------------------------------------------------
% Solar Module Used: SunPower SPR-305E-WHT-D
% Rated power at Standard Test Condition Irrstc=1000W/m^2, Tempstc=25oC
% Pnom = 305W/module
% Temperature Coefficient with power: Pcoef = -0.38%/K
% Estimate Power Calculation:
% P = Pnom*fpv*(Irr/Irrstc)*(1+a*(Temp-Tempstc))
% fpv: derating factor (assume to be 1), and no losses while connecting
% panels into an array
%-------------------------------------------------------------------------
Irrstc = 1000; % W/m^2
Tempstc = 25; % Celcius
Pcoef = -0.0038; % -0.38%
Pnom = xlsread('gen_para',1);% read the capacity of 2 PV generators
[~,genid] = intersect(Pnom(:,1),PVs_bus);
```

```
Pnom = (Pnom(genid,2)*1e6)';% The solar plant's capacities in Watt

%-------------------------------------------------------------------------
%The minute to minute solar irradiance and temperature data from NREL is
%compressed to T-minute time period by taking the mean
%-------------------------------------------------------------------------
Irr = xlsread('Solar_data',1,'C2:D721'); %read irradiance data
Temp = xlsread('Solar_data',2,'C2:D721');%read temperature data
[data_row data_col] = size(Irr);
if T ~= 1 % do not need to compress if period is 1 minute
    for k=0:(data_row/T)-1
        Irr(k+1,:) = mean(Irr(k*T+1:k*T+T,1:data_col));
        Temp(k+1,:) = mean(Temp(k*T+1:k*T+T,1:data_col));
    end
Irr(k+2:data_row,:)=[]; %irr.data after compressed to T-minute period
Temp(k+2:data_row,:)=[];%temp.data after compressed to T-minute period
end

%-------------------------------------------------------------------------
% State-space model of irradiance and temperature system for Kalman Filter
%-------------------------------------------------------------------------
% Irr = x1; Temp = x2; dIrr = u1; dTemp = u2
% x1(k+1) = x1(k) +   0   + u1(k) + 0     + w1    + 0
% x2(k+1) = 0     + x2(k) + 0     + u2(k) + 0     + w2
% y1(k)   = x1(k)
% y2(k)   = x2(k)
%-------------------------------------------------------------------------
F=[1 0;0 1];
B=[1 0;0 1];
H=[1 0;0 1];
Plant = ss(F,[B B],H,0,-1,'inputname',{'u1' 'u2' 'w1' 'w2'},...
                           'outputname',{'y1' 'y2'});
Q = [31.7 0;0 0.1]; % the process noise covariance(Q)
R = [10.5 0;0 0.5]; % sensor noise covariance(R)
[kalmf,~,~,~,~] = kalman(Plant,Q,R);
kalmf = kalmf(1:2,:);%interested in the output estimate y_{e}
SimModel = kalmf;
SimModel.inputname;
SimModel.outputname;

%-------------------------------------------------------------------------
% Generating noise, measurement and inputs
%-------------------------------------------------------------------------
t = (0:size(Irr,1)-1)';
rng(10,'twister');
v1 = real(sqrt(R(1,1)).*randn(size(Irr)));% irr. sensor error
v2 = real(sqrt(R(2,2)).*randn(size(Temp)));% temp. sensor error
y1v = Irr + v1;     % measured output
y2v = Temp + v2;     % measured output

%-------------------------------------------------------------------------
% moving average prediction for Irr input
%-------------------------------------------------------------------------
% real Irr input obtain from the sensor
ur1 = real(diff(y1v)); ur1 = [ur1(1,:);ur1];
% real Temp input obtain from the sensor
ur2 = real(diff(y2v)); ur2 = [ur2(1,:);ur2];
% initial guess of irr. input that forms a sin wave output
ui1 = [0;diff(sin(t*pi/t(length(t)))*Irrstc*0.9)]; ui1 = [ui1 ui1];
% initial guess of temp. input that forms a constant line output
ui2 = [[0 0];diff(sin(t*pi/t(length(t))))*mean(Temp)];
% the initial value x(0) of irr. and temp.
x10=[0 0]; % zeros for irr.
```

```
x20=[20 7]; % mean for temp.
% the predictive inputs of the system starts with initial guess
u1 = ui1;
u2 = ui2;
for k=3:length(t)
    u1(k,:) = (ui1(k,:) + ur1(k-1,:))/2;% moving average
    u2(k,:) = (ui2(k,:) + ur2(k-1,:))/2;% moving average
end

%--------------------------------------------------------------------------
% Run the Kalman Filter estimation
%--------------------------------------------------------------------------
for k=1:size(Irr,2)
    out = lsim(SimModel,[u1(:,k),u2(:,k),y1v(:,k),y2v(:,k)],...
                                                    t,[x10(k) x20(k)]);
    y1e(:,k) = out(:,1);  % filtered response, Irradiance
    y2e(:,k) = out(:,2);  % filtered response, Temperature
end
%prediction output of the next period usinng filtered response and the
%moving average input obtained above y1e->irr  y2e->temp
y1e = [y1e(1,:);y1e(1:length(y1e)-1,:) + u1(1:length(u1)-1,:)];
y2e = [y2e(1,:);y2e(1:length(y2e)-1,:) + u2(1:length(u2)-1,:)];

%--------------------------------------------------------------------------
% Estimation using PSS, simply delay 1 period
%--------------------------------------------------------------------------
Irrpss = [y1v(1,:);y1v(1:length(y1v)-1,:)];
Temppss = [y2v(1,:);y2v(1:length(y2v)-1,:)];

%--------------------------------------------------------------------------
% Calculating the Power from irradiance and temperature
%--------------------------------------------------------------------------
% Real Power generated
Preal = bsxfun(@times,Pnom,(Irr/Irrstc)).*(1+Pcoef*(Temp-Tempstc));

% Estimated Power from Kalmann Filter
Pkal = bsxfun(@times,Pnom,(y1e/Irrstc)).*(1+Pcoef*(y2e-Tempstc));
% power mismatch of Kalman filtering approach in kW
Pmm_kal = (Pkal - Preal)/1000;

% Estimated power using PSS
Ppss = bsxfun(@times,Pnom,(Irrpss/Irrstc)).*(1+Pcoef*(Temppss-Tempstc));
% power mismatch of PSS approach in kW
Pmm_pss = (Ppss - Preal)/1000; %

%--------------------------------------------------------------------------
% Plot
%--------------------------------------------------------------------------
% for generator 1
%--------------------------------------------------------------------------
Irr1_r = Irr(:,1);
Irr1_e = y1e(:,1);
Irr1_pss = Irrpss(:,1);
Temp1_r = Temp(:,1);
Temp1_e = y2e(:,1);
Temp1_pss = Temppss(:,1);
figure;
clf
subplot(311), plot(t,Irr1_r,'b',t,Irr1_e,'r--',t,Irr1_pss,'g-.',t,...
                    sin(t*pi/t(length(t)))*Irrstc*0.9,'k:','LineWidth',1),
ylim([-50 1000]),
xlabel('Irradiance'), ylabel('(W/m^2)'),
legend('Actual','Kalman Filter','PSS','initial guess'),
```

```
title(['Irradiance, Temperature and Power Comparision of PV at bus #' ...
                    num2str(PVs_bus(1)) '(' num2str(T) '-minute period)'])
subplot(312), plot(t,Temp1_r,'b',t,Temp1_e,'r--',t,Temp1_pss,'g-.',t...
                                ,x20(1)*ones(size(t)),'k:','LineWidth',1),
xlabel('Temperature'), ylabel('(oC)')
subplot(313), plot(t,Preal(:,1)/1e6,'b',t,Pkal(:,1)/1e6,'r--',t,...
                                        Ppss(:,1)/1e6,'g-.','LineWidth',1),
xlabel('Power'), ylabel('(MW)');

% Power mismatch in bar graph
figure;
subplot(211), bar(Pmm_kal(:,1)),
xlabel('Kalman Filter'), ylabel('mismatch(kW)'),
ylim([-3e4 3e4]),
title(['Power Deviation from the actual value at PV bus #' ...
                    num2str(PVs_bus(1)) '(' num2str(T) '-minute period)'])
subplot(212), bar(Pmm_pss(:,1)),
xlabel('PSS'), ylabel('mismatch(kW)'),
ylim([-3e4 3e4])

%-----------------------------------------------------------------------
% for generator 2
%-----------------------------------------------------------------------
Irr2_r = Irr(:,2);
Irr2_e = y1e(:,2);
Irr2_pss = Irrpss(:,2);
Temp2_r = Temp(:,2);
Temp2_e = y2e(:,2);
Temp2_pss = Tempps s(:,2);
figure;
clf
subplot(311), plot(t,Irr2_r,'b',t,Irr2_e,'r--',t,Irr2_pss,'g-.',t,...
                    sin(t*pi/t(length(t)))*Irrstc*0.9,'k:','LineWidth',1),
ylim([-50 1100]),
xlabel('Irradiance'), ylabel('(W/m^2)'),
legend('Actual','Kalman Filter','PSS','initial guess'),
title(['Irradiance, Temperature and Power Comparision of PV at bus #' ...
                    num2str(PVs_bus(2)) '(' num2str(T) '-minute period)'])
subplot(312), plot(t,Temp2_r,'b',t,Temp2_e,'r--',t,Temp2_pss,'g-.',t,...
                                 x20(2)*ones(size(t)),'k:','LineWidth',1),
xlabel('Temperature'), ylabel('(oC)')
subplot(313), plot(t,Preal(:,2)/1e6,'b',t,Pkal(:,2)/1e6,'r--',t,...
                                       Ppss(:,2)/1e6,'g-.','LineWidth',1),
xlabel('Power'), ylabel('(MW)');
% Power mismatch in bar graph
figure;
subplot(211), bar(Pmm_kal(:,2)),
xlabel('Kalman Filter'), ylabel('mismatch(kW)'),
ylim([-3e4 3e4]),
title(['Power Deviation from the actual value at PV bus #' ...
                    num2str(PVs_bus(2)) '(' num2str(T) '-minute period)'])
subplot(212), bar(Pmm_pss(:,2)),
xlabel('PSS'), ylabel('mismatch(kW)'),
ylim([-3e4 3e4])

end
```

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