Power Control Method Using Kalman Filter Prediction for Stable Operation of PV/FC/LiB Hybrid Power System Based on Experimental Dynamic Characteristics

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This paper focuses on controlling a real power system which includes 15 kW photovoltaic power source combined with 15 kW - 7.5 kWh lithium-ion battery and 10 kW proton exchange membrane fuel cell. A control method needs to be developed to ensure the power balance between the supply from the intermittent PV power and the demand at any instant. In this study, a power management unit associated with Kalman filter prediction and based on experimental dynamic characteristics of system components has been designed. The performance of system with implemented power management strategy for several typical days is evaluated through simulation. The simulation results show that this new control method is reliable in load satisfaction in a long term as well as in a short term. In addition, the proposed method, compared with conventional power management strategy, shows the benefit of using less hydrogen and therefore, higher efficiency in the simulation time.

Key Words
Photovoltaic power, Battery, Fuel cell, Power management strategy, Kalman filter

1. Introduction
In the context of fossil fuel depletion and the environmental concerns, renewable energy (RE) is widely used around the world as a promising alternative of the conventional energy due to their advantages of free availability, environmental friendliness and ability of installation in remote area. However, in order to overcome its drawback of intermittent nature, RE sources are always combined with other energy storages, such as battery and fuel cell (FC). Because the transient response of FC is slow while that of battery is faster, battery is used to cover the fluctuation. One of the most important problems in such a hybrid system is the control strategy to ensure the equality between the supply and the demand against the fluctuation of the RE sources. Initially studied by Ulleberg Ø., simple power management strategies (PMSs) in which the key decision factors were the power delivered by the RE sources and the state of charge (SOC) of battery were proposed. The PMSs were then further developed by using hysteresis band to prevent FC from frequent start-up and shut-down. However, because the PMSs were based on the real power and the SOC of battery to make decision which storage would operate, the sampling time must be long enough for the FC being able to work without error. Another approach for studying the PMSs is based on optimization of power
cost and the life time of storage devices. The cost optimization - based PMSs gained the economic benefit in the long run, but most of the studies used an hourly time interval for simulation, they had not taken into consideration the dynamic process of the system which is the behavior of the system when there is a sudden change of supply or demand. Moreover, due to the high capital cost of the system design and implementation, the previous researches were mainly based on theoretical models.

In this study, we proposed a new PMS considering the dynamic response of the components of the system and trend - prediction of supply - demand power that can work with real time power using short time interval. Based on experiments, the dynamic characteristics of devices were modeled. Due to its slow response, FC will operate with little changed power which is predicted while lithium-ion battery (LiB) with its ability of fast changing will work to compensate the deviation. The trend of the power will be predicted satisfying the dynamic response of the FC, allowing the use of shorter sampling time. For trend - predicting, Kalman Filter (KF) is used due to its ability to recursively estimate the state of a dynamic system without considering all the past data and easy adaptation to any alteration of the observations. Moreover, the changing rate of predicted time series can be adjusted by changing the parameter used in KF algorithm. The effectiveness of this new control method will be evaluated through simulation. In addition, the comparison between the performance of the system under KF-based PMS and conventional one was also carried out.

2. System Description and Components Dynamic Characteristics

A system consisting of 15 kW photovoltaic sources (PV) with 15 kW - 7.5 kWh LiB and 10 kW proton exchange membrane type (PEM) FC is currently installed as a part of the Carbon Neutral Energy System (CNES) at University of Tsukuba in Japan. The system can be used for commercial application. We suppose it is to supply to a constant load of 4.5 kW in this study. All the devices are combined together to a DC bus of 380 V through DC/DC converters. The system also connects to utility through AC/DC converter. The block diagram of the system is shown in Fig. 1. The 15 kW PV system used in the system consists of 84 NU-180LW type panels wiring in 12 series and 7 parallel. The PEM-FC with the power rating of 10 kW has been used. The LiB is SLPB60460330H module with the capacity of 7.5 kWh and maximum power of 15 kW. Other specifications of these devices are shown in Table 1.

The dynamic models of the LiB and the FC play important roles for dynamic control of the system. Therefore, the dynamic models of components have been built which were based on the experimental results on transient characteristics of the LiB and the FC with both DC/DC converters taken into consideration.

### Table 1 Specifications of equipment in the system

| PV array | PV Module | DC/DC |
|----------|-----------|-------|
| Maximum power | $P_{\text{max}}$ | 180 W |
| Open-circuit voltage | $V_{oc}$ | 30 V |
| Short-circuit current | $I_{sc}$ | 8.37 A |
| Voltage at MPP | $V_{\text{MPP}}$ | 237 V |
| Current at MPP | $I_{\text{MPP}}$ | 76 A |
| Temperature coefficient | $K_t$ | 0.053 %/C |

| FC stack | DC/DC |
|----------|-------|
| Input | Hydrogen | 90 LPM |
| Rate max | 124 LPM |
| Pressure 5 barg | |
| Output | DC 100 ~ 150 V | 380 V ± 40 V |
| 94 ~ 100 A | 0 ~ 25 A |
| Steady-state efficiency | 46% | 80% |
| LiB stack | DC/DC |
| DC 207 V | 37.5 A |
| Operating Voltage range | DC200 ~ 225 V | 380 ± 40 V |
| Operating Current range | 0 ~ 72.5 A | 0 ~ 37.5 A |
| Rated efficiency | 94.3% | 80% |
\[
\eta_{de} = \frac{P_{DC} \times \Delta t}{\Delta E_{H2,eq}} \times 100 \quad (1)
\]

where \(\eta_{de}\) (%) is energy conversion efficiency in \(\Delta t\) (s), \(P_{DC}\) is power at DC bus side of the converter at time \(t\) and \(\Delta E_{H2,eq}\) (kWh) is equivalent power of hydrogen in \(\Delta t\), which can be calculated as below:

\[
\Delta E_{H2,eq} = \frac{m_{H2} \times \Delta t \times p \times T}{C \times T} \times M \times LHV \times 10^{-3} \quad (2)
\]

where \(m_{H2}\), \(p\), \(T\) is mass flow (L/s), pressure (atm) and temperature (K) of \(H_2\) respectively, \(LHV\) is lower heating value of \(H_2\) (33 kWh/kg), \(M\) is molar mass of \(H_2\) (2.016 g/mol), \(C\) is gas constant (0.0821 Latm/(mol.K)).

### 2.2 Lithium-ion Battery

LiB has been widely used to smooth out the short-term output power fluctuations due to its ability of fast charging/discharging, high round-trip efficiency, long cycle life, etc. SOC of LiB is a critical parameter which can be estimated as a function of power generated or consumed by the following equation:

\[
SOC(t) = SOC(t-1) - \frac{P_{DC}(t-1) \times \Delta t}{E} \times \eta \quad (3)
\]

where \(SOC(t)\) (%) is the SOC at time \(t\), \(P_{DC}(t-1)\) is the power at the DC bus side of the converter at time \(t-1\), \(E\) (kWh) is the capacity of LiB, \(\eta\) (%) is the efficiency of the energy conversion, considering both charging/discharging efficiency of the DC/DC converter.

Based on the experimental results, approximated curves of the LiB combined with DC/DC converter’s dynamic characteristics were shown in Fig. 3. It can be realized that the transfer functions of the dynamic response of LiB and DC/DC stack are exponential decay in discharging process and combination of exponentially decaying cosine and sine wave in charging process. This might be due to the characteristics of the current control system inside the DC/DC converter using to connect LiB with the DC bus.

The dynamic processes of LiB with DC/DC converter when there is a required power change were obtained as:

For discharging transient process:

\[
P = \Delta P_{required} \times (1 - e^{-\frac{t}{0.0029}}) \quad (4)
\]

And for charging transient process:

\[
P = \Delta P_{required} \times \left[1-c^{-8.5} \cos (21.86t) + 0.023c^{-8.5} \sin (21.86t)\right] \quad (5)
\]

### 3. Prediction Control Method

Ensuring the load satisfaction under power sources’ fluctuations is the main objective of a PMS. Fig. 4 shows the conventional PMS which is called PMS1. This PMS is based on the difference between load demand and PV power, which is called \(P\), and the SOC of the LiB to make decision \(^8\)~\(^{13}\). In this study, we proposed PMS2 which includes a forecasting tool and a power management unit as illustrated in Fig. 5. In this method, the power for storages \(P\) will be predicted. The FC will generate this prediction value \(P_{pre}\) with or without offset depending on the SOC of the LiB. The FC will operate with \(P_{pre}\) minus offset when the SOC is high and plus offset when it is too small. The LiB takes the passive role to cover the deviation between the FC power and the real \(P\). Offset is introduced because the efficiency of the DC/DC converter can make the LiB to be deeply discharged during the operation if it only works to cover the fluctuation in a long time. The advantage of the proposed PMS is that it allocates the power to the FC and the LiB according to their dynamic characteristics. Therefore, the system can operate stably. Moreover, using KF can predict the trend of the stochastic time series and KF parameter can be suitably selected for the predicted

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**Fig. 2** The simulation result for dynamic process of the FC in case of changing power 0 kW - 5 kW - 3 kW

**Fig. 3** Dynamic characteristics of LiB when start discharging or charging
value satisfying the dynamic characteristics of storage, hence it can use the shorter interval of time to make decision than conventional one. Therefore, the offset to keep the SOC in case of no-prediction PMS must be higher than that of KF - based PMS. As a result, this can lead to the economic effectiveness when using less hydrogen.

An important issue needed to be considered in PMS2 is the forecasting tool. In order to predict the stochastic time series, there have been numerous approaches proposed in literatures, ranging from the traditional time series analysis such as autoregressive moving average (ARMA) models to recent approaches using artificial neural networks (ANN) [21] - [25]. These methods have the drawback of using numerous known data to determine and validate the model structural coefficients. With the presence of random disturbance in PV output as well as the limitation of power changing rate of FC, the use of an adaptive controller becomes necessary. For this reason, KF, which is a simple and optimal algorithm working online for linear systems with Gaussian noise is chosen for predicting in this study.

The state and measurement equations for the linear stochastic discrete - time system using state - space model are given by:

\[
\begin{align*}
    x_n &= F_{n-1} + G_{n-1} \\
    y_n &= H_{n-1} + v_n
\end{align*}
\]

where \( x_n \) and \( y_n \) represent state and the measurement (observation) at the moment \( n \), respectively. \( w_n \) and \( v_n \) denote process and measurement noises, which are assumed to be zero mean Gaussian white noise with covariance \( R \) and \( Q \), respectively. \( F \) and \( H \) are state transition matrix and measurement matrix of appropriate dimensions.

In this study, 2-dimension trend - Autoregressive (AR) model [26] was used for modeling the time series with assumption that \( y \) contains trend \( t \) as:

\[
\begin{align*}
    y_n &= t_n + v_n \\
    t_n &= 2t_{n-1} - t_{n-2} + w_n
\end{align*}
\]

The algorithm of KF including 2 stages can be illustrated as following:

Time Update: when the new observation value \( y_n \) is known, the estimate of \( x_n \) at step \( n \) will be calculated by:

\[
\begin{align*}
    x_n &= F_{n-1} + G_{n-1} F^T + G_{n-1} Q F^T \\
    P_n &= (I - K_n H) P_{n-1}
\end{align*}
\]

Measurement Update: when the new observation value \( y_n \) is known, the estimate of \( x_n \) at step \( n \) will be calculated by:

\[
\begin{align*}
    x_n &= x_n + K_n (y_n - F_{n-1}) \\
    K_n &= P_n H^T (HP_n H^T + R) \text{ }^T \\
    P_n &= (I - K_n H) P_n
\end{align*}
\]

In order to evaluate the effectiveness of the new control method, we compared the performance of the system under different control methods which are trend-AR model combined KF-based one and the no-prediction

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Fig. 4 The logical diagram in conventional PMS (PMS1) [8] - [13] (a) and the diagram of the proposed PMS (PMS2) and the block diagram inside the controller (b). \( P_L, P_{PV}, P_{FC}, P_{LiB} \) [W]: load, PV, FC and LiB power, respectively. \( P \) [W]: difference of load and PV power. \( P_{pre} \) [W]: prediction value of \( P \). SOC [%]: state-of-charge of LiB. SOCon and SOCoff: SOC to start-up or shut-down FC. SOC1 and offset1 are to make use of LiB capacity, SOC2, offset and offset2 are used to keep SOC not too small (SOC1 > SOC2).
Fig. 5 The PV power using for simulation, difference between load and PV power, $P = P_L - P_{PV}$, the changing rate of $P$ in the 1st day (a), the 2nd day (b), the 3rd day (c) and the 4th day (d)
Table 2 The analyzed data of PV power changing rate and PV energy in the days for simulation

| Day | PV energy (kWh) | P_{PVmax} max (W/s) | P_{PVmin} min (W/s) | P_{PVmean} average (W/s) | P_{PVmean} (W/s) at accumulate probability of 99.5% |
|-----|-----------------|---------------------|---------------------|-------------------------|-----------------------------------------------|
| 1st | 55.21           | 870                 | -1872               | 48                      | 288                                           |
| 2nd | 26.8            | 600                 | -1148               | 97                      | 594                                           |
| 3rd | 49.03           | 199                 | -183                | 41                      | 155                                           |
| 4th | 66.5            | 404                 | -994                | 41                      | 231                                           |

4. Simulation Results and Discussions

The performance of the system with the proposed control method was simulated in a time period of 4 typical days as shown in Fig. 5 and Table 2, namely the first day (1st day) with high energy and moderated PV power changing rate, the second day (2nd day) with large fluctuation of PV power, the 2nd day also has no redundant power, the third and fourth day with little (3rd day) and much (4th day) redundant power, respectively. The data with sampling time of 3s was used for KF-based PSM while in no-prediction-based PMS, 60s-time intervals was used for making decision.

The measurement noise covariance R0 was estimated of 0.1 using the maximum log-likelihood and based on the real past PV power series. The selection of KF parameter, e.g. the process noise covariance Q, were carried out to guarantee the FC power changing rate smaller than the limit of 100 W/s that FC can operate and to consume small amount of hydrogen. The effect of Q on the fluctuation of FC power is shown in Fig. 6. It shows that the larger Q is, the more strongly the FC power fluctuates. Table 3 presents the maximum, minimum FC power changing rate and the hydrogen amount corresponding to Q. The hydrogen amount and the power changing rate will decrease when Q decreases. When Q is smaller than $3 \times 10^{-7}$, the FC power will moderately fluctuate with the rate below 100 W/s. However, the amount of hydrogen changes insignificantly around this value. Therefore, $3 \times 10^{-7}$ was chosen as the suitable value of Q that the FC can operate with the maximum changing rate of 96 W/s close to its real maximum ability of changing power of 100 W/s.

Fig. 7 shows the performance of the system in the case of Q = $3 \times 10^{-7}$. From the results, it can be realized that the power designated to the FC changes little while the power for the LiB strongly fluctuates. This is due to the application of the trend-AR model and KF-based control method which can predict the trend-power that varies slightly. In other words, the power will be divided into 2 parts, one gradually changes which will be forecasted by KF and generated by the FC and the other one drastically fluctuates which will be covered by the LiB. Therefore, each device can contribute its part to generate the needed power depending on its dynamic characteristic. With the selection of Q of $3 \times 10^{-7}$, the FC power changing rate is close to 100 W/s, thus the FC can operate without any problems. In addition, it remains keeping the initial value of 25% over the 4 days, so the LiB can operate in a long time.

In order to keep the SOC not to deeply decrease, the offset in the case of PMS1 was higher than offset2 of KF-based PMS. This in turn had influence on the amount of hydrogen. Table 4 summarizes the hydrogen volume needed for each day in 2 cases. It can be realized that the system consumed less hydrogen when using KF-based method, especially in the 2nd day which is the day lack of power and the FC has to work all day long. During other days, the
KF-based PMS had insignificant effectiveness in comparison with PMS1 because in these days, the FC worked when the power changed slightly hence the FC operated with little changed power.

The overall efficiency of the system can be calculated as below:

\[ \eta_{\text{sys}} = \frac{\int_0^T P_t \, dt}{\int_0^T P_{PV} \, dt + E_{H2} + E_{\text{LiB}}^{\text{final}} - E_{\text{LiB}}^{\text{initial}}} \]  

in which \( E_{H2} \) (kWh) is the equivalent energy of hydrogen consumed by the FC in period time \( T \) (s) which is calculated by equation (2), \( E_{\text{LiB}}^{\text{final}} \) and \( E_{\text{LiB}}^{\text{initial}} \) are the energy in LiB at initial and final time of simulation.

The system efficiency for 4 days was estimated and summarized in Table 4. It can be seen that the KF-based PMS has a slightly higher overall efficiency than conventional PMS.

Voltage is an important parameter to assess a power system quality. Therefore, DC bus voltage was examined to evaluate the effectiveness of the proposed control method. For simplicity, the load was considered as a resistor and represented by a resistance \( R \) (Ω) which is calculated by \( V_{DC}^2 / P_L \). In this paper, the system is assumed to supply to the constant load of 4500 W through DC bus voltage of 380 V, the resistance \( R \), therefore, is calculated of 32.09 Ω. The DC bus voltage was then simulated by the following equation:

\[ V = \sqrt{\left(P_{PV} + P_{\text{LiB}} + P_{FC}\right)^2 / R} \]  

Fig. 8 shows the DC bus voltage in 4 days using 2 PMSs. Assumed that PV power changes from one value to another in a short time \( \Delta t \) then keeping this value in a sampling time of 3 s before changing to other one as shown in Fig. 8a. With the maximum \( \Delta P \) of 5616 W (in the 1st day), the DC bus voltage when the sudden change of power occurs in short time \( \Delta t = 250 \) ms was within a range of \( \pm 10\% \) (Fig. 8b, b') which is the acceptable range for DC/AC converter working to supply to the load. The shorter the changing time \( \Delta t \) is, the larger the voltage will

### Table 4 Comparison of amount of hydrogen and efficiency using 2 PMSs

| Method       | Amount of hydrogen, Nm³ | Overall efficiency (%) |
|--------------|--------------------------|------------------------|
| 1st day      | 2nd day                  | 3rd day                | 4th day    | 4 days |
| No–prediction PMS1 | 57.066                  | 81.212                 | 66.444     | 58.490 | 263.211 | 45.14 |
| KF PMS2      | 56.826                   | 79.846                 | 65.535     | 58.410 | 260.617 | 45.55 |
Fig. 8  The assumed changing process of power (a), the DC bus voltage in simulation time period under 2 PMSs: conventional PMS (black line - (b), (c), (d), (e)) and KF-based PMS (blue line - (b'), (c'), (d'), (e'))
be. With higher changing power, longer occurring time is needed. This voltage changing was occurred due to the transient characteristic of the DC/DC converter for the LiB. To diminish the voltage fluctuation, it needs to boost up this characteristic. This can be done by using simple controller such as proportional-integral-derivative (PID) or model predictive controller (MPC). The simulation results for other days shows that under both 2 PMSs, the DC bus fluctuated slightly and can supply to the load stably. In the 2nd day when the PV power changed strongly, the voltage fluctuated within -5.8% to 3.2%, while the 3rd day in which the PV changing power was small, the DC bus voltage slightly fluctuated around ±1%. The 1st day and the 4th day witnessed a suddenly considerable decrease of voltage at an instant to -10% and -9.2% respectively. As mentioned above, these sudden changes were caused by the sudden changes of power that were assumed by error. However, with these unexpected changes, the DC bus voltage was still within its accepted working voltage range (±10%). Comparing 2 cases of methods, there is no considerable difference between the DC voltages in general. However, at some instants, the proposed PMS shows less fluctuated voltage than conventional one, for example, at time 11:42:30 of the 2nd day as shown in Fig. 9. As mentioned above, the offset in case of no-prediction PMS is larger than that of KF-based one. As a result, LiB had to charge in PMS1 more than in PMS2. In addition, the dynamic characteristic of charging process is slower than discharging. Therefore, when the LiB changes its power during charging (Fig. 9b), its ability to cover the deviation between the FC power and the real needed power is worse than discharging, resulting in more fluctuated voltage (Fig. 9c).

5. Conclusions

This paper presents a new control method based on trend-AR model KF prediction for the hybrid renewable system and storages. The new proposed method was evaluated by simulation during a time period of typical days. The simulation results show that with suitable value of KF parameter, the proposed control method can be applied to the PV/LiB/FC system for stable operation in a short time as well as in a long time. In comparison with conventional PMS, it can give not only a better stability in performance in some cases, but also more economically effective performance.

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