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APPLICATION OF KALMAN FILTER IN MAXIMUM POWER POINT TRACKING OF SOLAR PHOTOVOLTAIC CELL

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ABSTRACT:- *This paper proposes implementation of a new MPPT technique using Kalman Filter. The approach uses Kalman filter algorithm to track maximum power point. Using this approach tracking becomes much faster than using the generic Perturb & Observe algorithm in case of sudden weather changes. Experimentation was performed under optimal conditions as well as under cloudy conditions i.e. falling irradiance levels. Using the proposed technique the maximum power point of a solar PV array is tracked with an efficiency of 97.11%. Moreover, the maximum power point has been tracked at a much faster rate i.e. 4.5 ms using the proposed algorithm compared to the existing generic Perturb and Observe approach.*

Keywords-*Maximum power point tracking, Kalman filter, perturb and observe, photovoltaic etc.*

INTRODUCTION

As the global concern about the negative impact generated from conventional energy sources increases, various research and development on the renewable energy have become the primary task for all scientists and engineers. Among all types of renewable energy, solar energy is the most favorable alternative and has been widely utilized in industrial electrical generation or stand-alone applications. The popularity of solar energy is contributed by its sustainability, cleanliness, ease of maintenance and absolute zero noise characteristics .In order to fulfill high demand of energy usage, especially in a developing country like India, exploitation on sustainable energy is inevitable. The Ministry of Energy, Water and Communication has indicated that solar energy will be one of the most important renewable sources in India, thanks to the location of India which is near to the equator where abundant sunshine can be obtained. Numerous policies have been conveyed to safeguard long-term reliability of energy resources for sustainable development in the country. Solar energy [1] is one of the most widely used sources of renewable energy and is available in abundance. Solar radiation is converted to electrical energy by using solar cells which exhibit photovoltaic effect. Photovoltaic power is used in a variety of applications such as power generation, mobiles, computers and transportation applications. These PV solar panels [2] exhibit non linear V - I characteristics as their output supply depends mainly on the nature of connected load. Moreover there exist multiple maxima in the output characteristics of a solar PV array under partially shaded conditions. Hence, it is essential to find optimal power point of the panel so as to increase the overall efficiency of the photovoltaic system. Hence, Maximum Power Point Tracking (MPPT) algorithm [3] is used for extracting maximum power available from a PV module under different conditions. Various MPPT techniques [4] have been used in past but Perturb & Observe (P&O) algorithm is most widely accepted and preferably used by industry. Using P&O algorithm [5] the controller adjust voltage and measures power and if this measured power is greater than the previous value of power, adjustments are made in the same direction until there is no more increment in power . Fig. 1 shows how power is calculated using P&O algorithm. P&O is also called as hill climbing method because it checks the rise of the curve till MPP[6] and the fall after that point. This method is easy to implement but can cause oscillations in power output and can sometimes show tracking failures in rapid environmental changes i.e. locates operating point away from MPP when there is a sudden change in voltage characteristics.

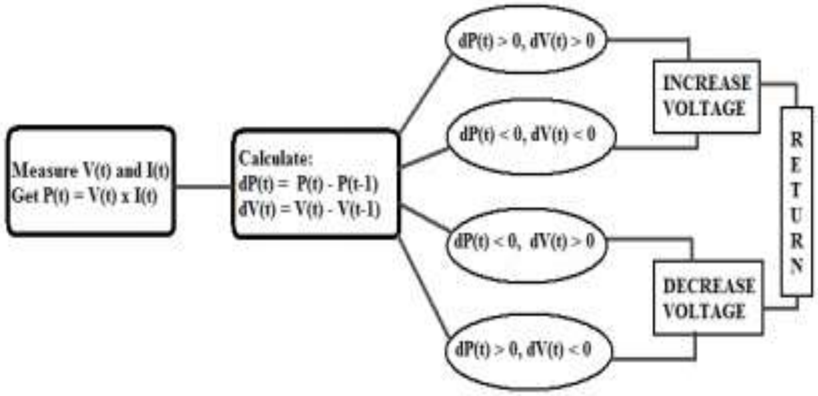

Figure 1 Flowchart depicting the Perturb & Observe algorithm

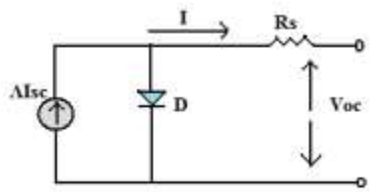

Figure 2 Solar cell equivalent circuit

This paper proposes implementation of a new MPPT technique using Kalman Filter.

LITERATURE REVIEW

The Kalman filtering is an optimal estimation method that has been widely applied in real-time dynamic data processing. A Kalman filter estimates the state of a dynamic system with two different models namely dynamic and observation models. The dynamic model describes the behaviour of state vector, while the observation model establishes the relationship between measurements and the state vector. Both models are associated with statistical properties to describe the accuracy of the models. For many applications, the model statistic noise levels are given before the filtering process and will maintain unchanged during the whole recursive process. Commonly, this a priori statistical information is determined by test analysis and certain knowledge about the observation type beforehand. If such a priori information is inadequate to represent the real statistic noise levels, Kalman estimation is not optimal and may cause to an unreliable results, sometimes even leads to filtering divergence (Mohamed and K.P. Schwarz 1999).For vehicle navigation, sudden acceleration or deceleration and sudden change of the directions are impossible to predict. Therefore it is difficult to design a system with constant noise variances that will satisfy all situations. One of the common problems with vehicle navigation using Kalman filter [7] is so called 'over shooting' problem. That is the effect that the dynamic model keeps position estimation along with previous trend while a vehicle actually turns to another direction.Adaptive filtering is trying to determine the statistic parameters of the dynamic system based on the behavior of the system during data processing, and it has been paid much attention in Kalman filtering theory (Jia and Zhu,1984, and Gustafsson, 2000). Different adaptive Kalman filtering algorithms have been studied for surveying and navigation applications. Chen (1992) and Mohamed and Schwarz (1999) applied adaptive Kalman filters for the integration of GPS and inertial navigation system (INS). Wang et al (1997) applied a simplified adaptive algorithm in kinematic GPS positioning. Chen et al (1999) uses adaptive filters to estimate the velocity of permanent GPS stations.

MPPT USING KALMAN FILTER

For nonlinear dynamics, system and observation noise cannot be separated without the knowledge of dynamics and observation function. An adaptive filter seeks to estimate the noise parameters as a part of the filtering process, and the ultimate goal of adaptive filtering is to find the covariance matrices Q and R thereby optimizing the filter performance. An adaptive filter can recover the correct covariances and can improve the filter performance for data assimilation problems.

Conventional Kalman filter

The linear discrete Kalman filter[8] for state dynamic and measurement models can be expressed as follows:

$X_k = = \phi_{k-1}\, x_{k-1} + w_{k-1}$ (1)

$Z_k = H_k x_k + v_k$ (2)

x_k is the (n × 1) state vector;

ϕ_k is the (n × n) transition matrix;

Z_k is the (r × 1) observation vector;

H_k is the (r × n) observation matrix;

w_k and v_k are uncorrelated white noise sequences with the following mean and covariance:

$E\{w_k\} = E\{v_k\} = 0$ (3)

$E\{v_k^T\} = 0$ (4)

$E\{wk\ w_k^T = Q_k, (i = k)$

$0, (i \neq k)$ (5)

$E\{vk\ v_k^T\} = R_{k\,,}(\mathrm{i} = \mathrm{k})$

$0, (i \neq k)$ (6)

$E\{.\}$ denotes the expectation function; Q and R are the covariance matrix of process noise and measurement errors respectively.

The Kalman filter [9] state prediction and state covariance prediction are:

$\bar{x}_k = \Phi_{k-1}\hat{x}_{k-1}$ (7)

$\bar{P}_k = \Phi_{k-1}\hat{P}_{k-1}\Phi_{k-1}^T + Q_{k-1}$ (8)

$\hat{x}_k$ denotes the state estimated state vector;

$\bar{x}_k$ is the predicted state vector for the next epoch;

$\hat{P}_k$ is the estimated state covariance matrix;

$\bar{P}_k$ is the predicted state covariance matrix.

The Kalman filter update steps are as follows:

$K_k = \bar{P}_k H_K^T\ (\ H_k\bar{P}_k H_k^T\ + R_k)^{-}1$ (9)

$v_k = Z_k - H_k\bar{x}_k$ (10)

$\hat{x}_k = \bar{x}_k + K_k\ v_k$ (11)

$\hat{P}_k = (I - K_k H_k)\bar{P}_k$ (12)

K_k is the Kalman gain , which defines the updating weight between the new measurements and the prediction from the system dynamic model.

Adaptive estimation of covariance matrices *Q* and *R*

The covariance matrices Q and R could be estimated using Minimum Norm Quadratic Unbiased Estimation (MINQUE) which is not suitable for real-time kinematic positioning (Wang, 1999). The method has been employed to estimate such matrices since it has very well-defined properties. One of the drawbacks of this method is that it requires iterative procedures which depend on the properties of the data and the model themselves (Wang et al, 1999). Therefore, it is unsuitable for real-time kinematic positioning. In online stochastic modelling, however adaptive Kalman filtering techniques can be adopted since they provide online estimation of dynamic and measurement noise covariance matrices Q and R respectively. One of the adaptive Kalman filtering techniques is covariance matching which makes the elements of the innovation or residual-based covariance matrix consistent with their theoretical values (Maybeck, 1982). The estimated covariance matrix of the innovations or residuals should match its theoretical form. The innovation which is the difference between the real observations and its predicted value can be computed as follows :

$v_k = Z_k - H_k\bar{x}_k$ (13)

The residual $\bar{v}_k$ which is the difference between the real observations and its estimated values can be expressed as:

$\bar{v}_k = Z_k - H_k\hat{x}_k$ (14)

Based on the above assumption, the philosophy of estimating Q and R matrices takes one of these following scenarios:

a) Fixing Q and varying R by trial and error until the realisitic values are found that give stable state estimates. In this case the Q matrix should be completely known;

b) Varying Q matrix if R is completely known and fixed to the certain value, otherwise;

c) Varying Q and R simultaneously, in this case none of them is known and the initial values for both matrices should be selected carefully in order to find the best stable estimate.

(a)Adaptive estimation of *R* based on innovation sequences

Following the procedures proposed by (Mehra,1970,1971; Mohamed and Schwarz, 1999; Yang and Xu, 2003), the measurement noise covariance matrix R can be adapted based on the innovation sequences as:

$$\hat{R}_k=\hat{C}_v - H_k\bar{P}_k H_k^T \qquad (15)$$

Where $\hat{C}_v$ computed through averaging inside a moving window of size m at epoch k (Mohamed and Schwarz, 1999):

$$\hat{C}_v=\frac{1}{m}\sum_{i=1}^{m} v_{k-i}\, v_{k-i}^T \qquad (16)$$

(b) Adaptive estimation of *R* based on residual sequences

When implementing the innovation based estimation for R as in equation (15), the outcomes must be positive definite. However, this outcome is not guaranteed since two positive definite matrices are subtracted. Therefore, Wang et al. (2000) proposed the residual based estimation for R in order to get positive definite outcomes. In this case the R matrix takes the following form (Wang et al, 1999):

$$\hat{R}_k=\hat{C}_{\bar{v}} + H_k^T\, H_k\hat{P}_k \qquad (17)$$

Where $\hat{C}_{\bar{v}}$ is calculated as:

$$\hat{C}_{\bar{v}}= \frac{1}{m}\sum_{i=1}^{m} \bar{v}_{k-i}\, \bar{v}_{k-i}^T \qquad (18)$$

(c) Adaptive estimation of *Q*

Estimation of the dynamic noise covariance matrix Q is linked with measurement noise covariance matrix R since estimation of R requires the predicted state covariance $P_{\bar{k}}$ and hence Q. Based on covariance matching principles, R is estimated using innovation or residual series based on Equations (15) or (17).
If R and are assumed to be known, Q can be scaled through calculating the ratio between the estimated innovation covariance and the predicted one (Din get al, 2007);

$$\alpha = \frac{trace\{\hat{C}_v-\hat{R}_k\}}{trace\{H_k^T - H_k\hat{P}_k\}} \qquad (19)$$

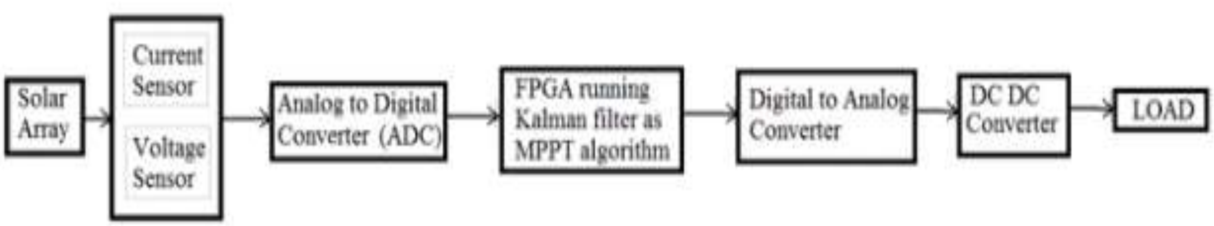

Figure 3 System setup (Block level)

RESULTS AND DISCUSSION

The error approximation of current sensor, voltage sensor and the quantization error according to ADC gives total measurement noise around 0.5% of maximum voltage so R is 0.1. M (the step size corrector) is selected on the basis of voltage change limitation and slope of the P – V curve. According to calculation M comes out around 0.05. The process noise Q has a chance to include high system noise and parameter uncertainty so has been taken as 0.2 here.

SIMULATION RESULTS WITH LINEAR KALMAN FILTER

Fig. 4 depicts the convergence of proposed MPPT algorithm [10] at optimal conditions (i.e. 250C and 1kW/m2) with the time of convergence around 4.5 ms. Simulation has been carried out using MATLAB 2009 according to power shown in Table .

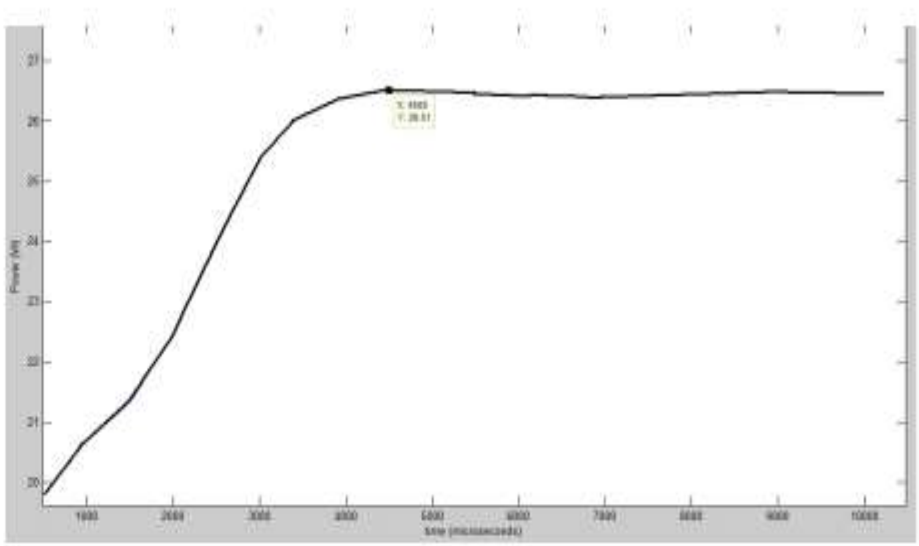

Figure 4 Convergence of proposed algorithm at 1kW/m2 irradiance and T = 250C.

TABLE Voltage and Power at falling irradiance level

Voltage		Current	Power
Actual(V)	MPPT(V)	A	MPPT(W)
20.51	20.75	0.92	19.48
20.33	20.62	1.00	20.62
20.20	20.43	1.03	21.05
19.97	20.30	1.06	21.52
19.85	20.21	1.05	21.22
19.66	20.10	0.82	16.48
19.52	20.02	0.68	13.62
19.46	19.97	0.55	10.98
19.30	19.88	0.52	10.34

CONCLUSION

In case of Maximum Power Point Tracking, it can be concluded that both these approaches are better than generic P&O algorithm approach which is only 96% efficient and takes 15 ms to converge to maximum power point and hence consumes less power. Thus it can be concluded that prediction and correction Kalman Filter algorithm proves fruitful in case of both the applications.

REFERENCES

[1] Hua Chihchiang, Lin Jongrong, Shen Chihming. Implementation of a DSP-Controlled Photovoltaic System with Peak Power Tracking. *IEEE Transactions on Industrial Electronics.* 1998; 45: 99-107.

[2] Chiu Chian-Song. T-S Fuzzy Maximum Power Point Tracking Control of Solar Power Generation Systems. *IEEE Transactions on Energy Conversion.* 2010; 25: 1123-32.

[3] Chiu Chian-Song, Ouyang Ya-Lun. Robust Maximum Power Tracking Control of Uncertain Photovoltaic Systems: A Unified T-S Fuzzy Model-Based Approach. *IEEE Transactions on Control Systems Technology*. 2011; 19: 1516-26.

[4] A. Johari, S. S. Hafshar, M. Ramli, H. Hashim. *Potential Use of Solar Photovoltaic in Peninsular Malaysia*. 2011 IEEE First Conference on Clean Energy and Technology (CET). 2011: 110-114.

[5] A. Y. Azman, A. A. Rahman, N. A. Bakar, F. Hanaffi, and A. Khamis. *Study of Renewable Energy Potential in Malaysia*. 2011 IEEE First Conference on Clean Energy and Technology (CET). 2011: 170-76.

[6] Hoe Choo Kian, A. C. Vaithlingam, R. Teymourzadeh, R. Rajkumar. *Design of Automatic Soil Humidity Control Using Maximum Power Point Tracking Controller*. 2010 IEEE Student Conference on Research and Development (SCOReD). 2010: 387-391.

[7] H. L. Tsai, C. S. Tu, Y. J. Su. *Development of Generalized Photovoltaic Model Using MATLAB/SIMULINK*. Proceedings of the World Congress on Engineering and Computer Science (WCECS). October 22 - 24, 2008.San Francisco, USA.

[8] T. Esram, P.L. Chapman. Comparison of Photovoltaic Array Maximum Power Point Tracking Techniques. *IEEE Transactions on Energy Conversion*. 2007; 22(2): 439-449

[9] V. Salas, E. Olías, A. Barrado, and A. Lázaro. Review of the Maximum Power Point Tracking Algorithms for Stand-Alone Photovoltaic Systems. *Solar Energy Materials and Solar Cells.* 2006; 90: 1555-1578

[10] I. Abdalla, L. Zhang, and J. Corda. *Voltage-Hold Perturbation &Amp; Observation Maximum Power Point Tracking Algorithm (Vh-P&O MPPT) for Improved Tracking over the Transient Atmospheric Changes*. Proceedings of the 2011-14th European Conference on in Power Electronics and Applications. 2011: 1-10.

