



**MAXIMUM POWER-POINT TRACKING USING THE EXTENDED KALMAN
FILTER ALGORITHM UNDER UNIFORM AND PARTIAL SHADING
CONDITIONS**

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ABSTRACT

The objective of this project is to track the maximum power point (MPPT) of the photovoltaic module using an Extended Kalman Filter. Perturb and Observe algorithm is the most widely used concept in the case of maximum power-point tracking due to its simple implementation. The issue with Perturb and Observe algorithm is that it has a slower tracking rate due to the method of removing the noise it uses. Hence, a new mathematical model has been introduced based on Kalman Filtering^{[16][1][11]}.

The Kalman filter uses a recursive computation method to estimate the states of the system, which is advantageous in minimizing the mean squared error and providing precise estimation though the model is anonymous. The Kalman Filter is only applicable to a linear system environment, but, the systems in the real world tend to have non-linear characteristics in nature. Therefore, a new set of equations was introduced exclusively to tend to the non-linearity problem of the systems. This type of filtering was called the Extended Kalman Filter^{[1][16]}.

The proposed filtering method is used to track the maximum power of the solar model by minimizing the effect of non-linearities under normal and partially shaded conditions. The results and performance of the system are compared with that of the Kalman Filter algorithm which shows that the EKF shows a better performance than that of the Kalman filter in a constantly changing environment^{[1][16][14]}. The algorithms and analyses are done in the MATLAB/Simulink environment and, the simulation and theoretical results are verified.

Acknowledgments

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INTRODUCTION AND MOTIVATION

Fossil fuels have been the ultimate source of energy for so many years, but continuous usage has led to the depletion of fossil fuels. The disadvantage of fossil fuels is that it takes years to get generated. Hopefully, there's been an increase in the usage of alternative renewable sources of energy such as solar, wind, tidal, biogas, and so on.

The photovoltaic module uses a tracking algorithm to find the optimal power called the maximum powerpoint. This point differs depending on various external factors like irradiance, temperature, and load resistances. There has been a huge increase in the use of the PV modules in various applications like generating solar energy, charging a battery, space-craft applications, and so on ^[1].

The PV panel model is considered to have the inputs as temperature and irradiance, the outputs as the voltage, current, and power.

1.1 PV MODULE

A photovoltaic panel is made by connecting several photovoltaic cells in series or parallel or in both ways depending on the requirement of the system. Then, the module is connected to a bypass diode to protect it from the damages caused by the heat.

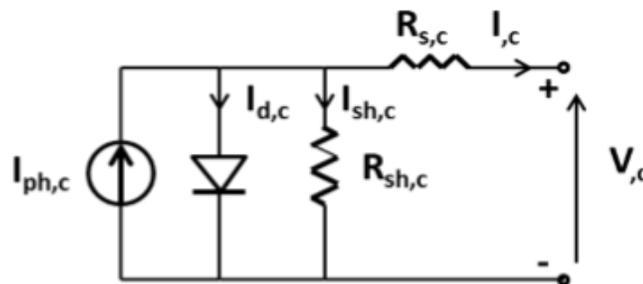


Figure 1: Equivalent Circuit of PV Module^[19]

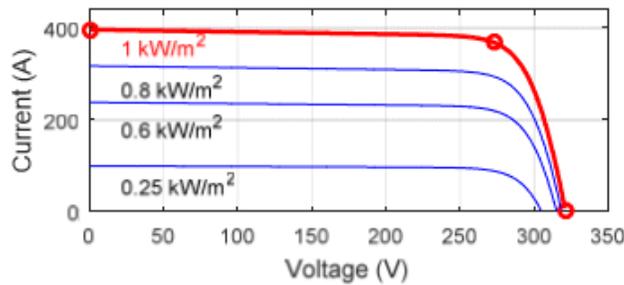
Fig 1. represents the equivalent circuit of the solar cell. Based on the P-N junction characteristics, the diode is added parallel to the DC current generator and connected to two resistors, R_s in series and R_{sh} in parallel. The voltage across the diode is V_D . V is the output voltage of the cell, and I is the load current.

By using Kirchoff's Current Law ^[5],

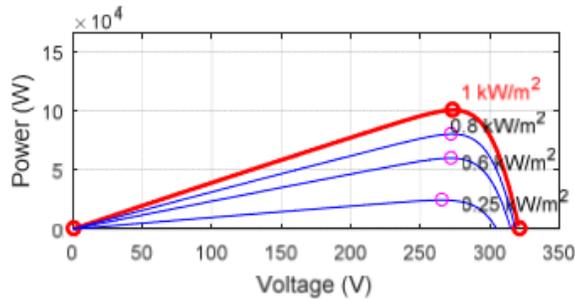
$$I = I_{ph} - I_s \left(e^{\frac{vd}{\eta V_T}} - 1 \right) - \frac{V_D}{R_{sh}}$$

..... (1)

Due to the non-linear characteristic of the photovoltaic cells, the PV characteristics of the module with varying irradiance levels and a constant temperature is as given in figure 2 (a) and (b) below,



(a)



(b)

Figure 2: MPPT of the PV cell^[12]

The non-linearity exists due to the constantly changing parameters like temperature, radiations and the load. From the figures above, it can be observed that each curve has an operating point, leading to maximum power. Also, at a uniform irradiance level, there exists only one maximum powerpoint. If there is a non-uniform irradiance level or change in temperature, it may lead to a different condition which is discussed in the following section.

1.2 PARTIAL SHADING

When a PV module is exposed to different levels of irradiation, the output leads to numerous peaks of maximum power points which are categorized as local maximum power points and global maximum power points. Hence, the shading condition causes difficulty in finding the optimum output power.

The fig. (3), shows the P-V characteristic comparison of the PV module under normal and shaded conditions.

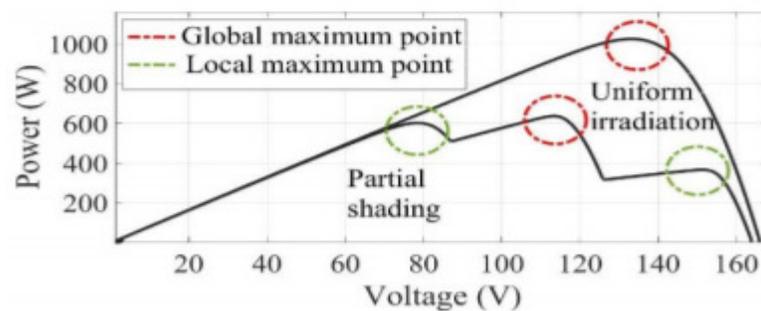


Figure 3:PV curves comparison under uniform and partially shaded conditions^[20]

It is observed from the above fig.(3), that the partial shading produces multiple peaks causing difficulty in tracking the maximum power-point.

1.3 MAXIMUM POWER-POINT TRACKING

The maximum power-point tracking (MPPT) is basically an electronic tracking, making the solar module operate at the most efficient voltage. Its algorithm is included in the charge controllers, leading to the extraction of the maximum power available from the photovoltaic module. The maximum power varies with the changing environment^{[11][12][11]}.

The charge controller compares the output of the solar panel and compares it to the voltage of the battery and converts its best power to get an efficient voltage to run the system. The conditions under which the MPPT works the best are at cold temperatures and when the battery discharges^{[1][12][16]}.

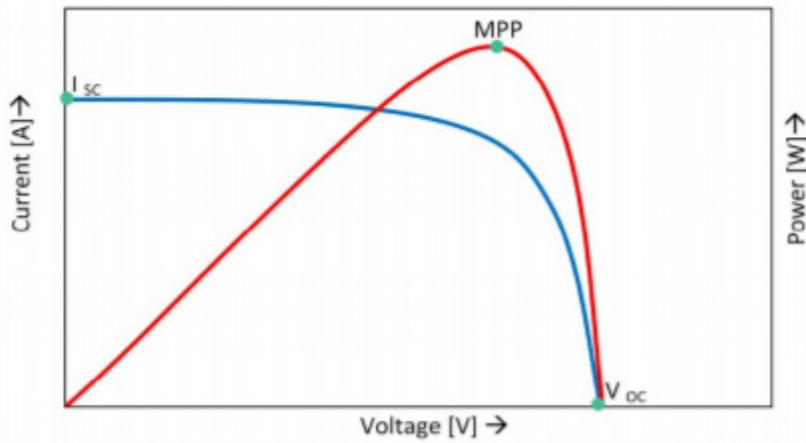


Figure 4: I-V curves of solar module^[17]

The above fig. (4), represents the I-V and P-V characteristics of a photovoltaic cell, clearly showing a single point in the power curve leading to a maximum power.

2. THEORETICAL BACKGROUND

The Maximum Power-Point can be tracked using various methods such as^{[12][11][8]}:

- Perturb and Observe(P&O): The most commonly used technique due to its simplicity. It depends on adjusting the voltage by a certain amount and the power is measured.
- Incremental Conductance: It makes use of computation method to measure the power, by comparing the incremental conductance to that of the PV modules conductance. If both the conductances are equal, the maximum power is obtained.
- Temperature method: Estimates the maximum voltage by measuring the temperature of the panel against the reference value.

And other techniques like current sweep, and constant voltage but, there are various other algorithms used to track the MPP such as the particle swarm optimization (PSO), where the problem is optimized by the iterative computation method to improve the efficiency of the particles. Also, fuzzy logic control is considered a better one as it can clearly differentiate between multiple power points at certain conditions.

Though there are several techniques, perturb and observe algorithm is the most widely used technique, by adjusting the voltage and comparing the previous and current output power as shown in the flowchart and fig. (5) and (6) below. But the P&O technique and others were observed to have a slower tracking response. Therefore, Kalman Filter has been introduced to improve the efficiency and the tracking rate.

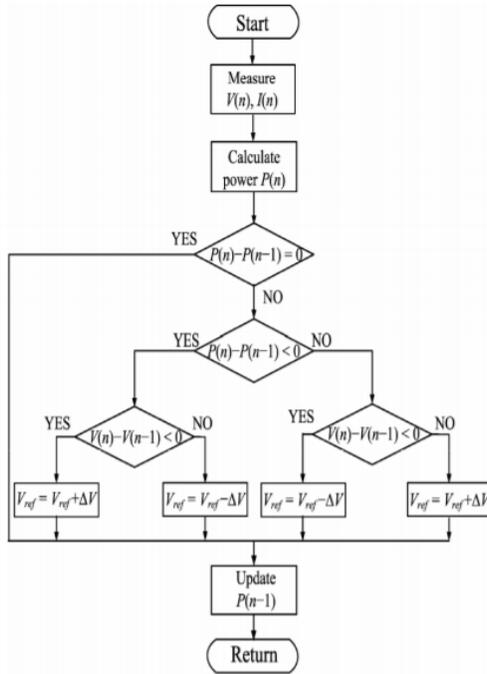


Figure 5: Perturb and Observe algorithm^[11]

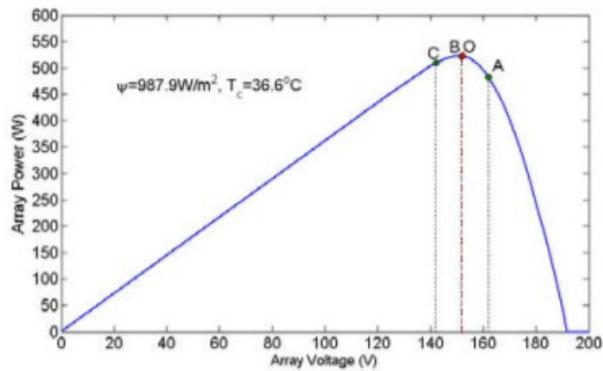


Figure 6: P-V curve using P&O method^[11]

2.1 KALMAN FILTER

The Kalman Filter is a recursive computation method of a set of differential equations and estimate the state of a process, that minimizes the minimum mean squared error. The advantages of the Kalman filter are that it can predict the states of the system (all past, present and the future), also gives the precise estimation of the unknown system.

Considering a discrete time-controlled process, represented by a set of differential equations for estimating the state 'x' is written as given below^[16],

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \dots \dots \dots (2)$$

Where, A and B are nXn matrices,

x_k is estimate at the current time step k,

x_{k-1} is the previous estimate at time k-1,

u_{k-1} is control input,

w_{k-1} represents the process noise

The measurement equation is given by,

$$z_k = Hx_k + v_k \dots \dots \dots (3)$$

Where z_k represents the measurement

H denotes the mXn matrix that changes at each time step

V_k denotes the measurement noise

The Kalman Filter makes use of the predictor-corrector algorithm, which use a certain feedback control. The equations for the filter are put into two categories as time update and measurement update equations. The time update is also called as predictor equations and the measurement update is also called as corrector equations.

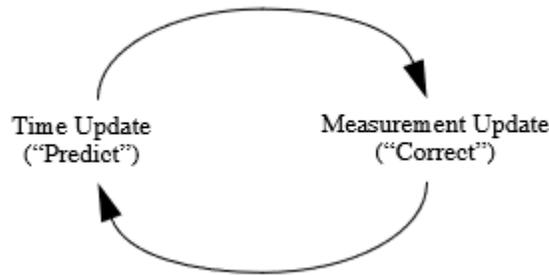


Figure 7:Kalman Filter (Predictor-Corrector) Algorithm^[16]

The equations for the time and measurement updates are represented in the tables (1) and (2) below,

Table 1: Predictor equations of Kalman Filter^{[5][16]}

TIME UPDATE(PREDICT)
<ol style="list-style-type: none"> 1. $x_{k-} = Ax_{k-1} + Bu_{k-1}$ 2. $P_{k-} = AP_{k-1}A^T + Q$

Table 2: Corrector equations of Kalman Filter^{[5][16]}

MEASUREMENT UPDATE(CORRECT)
<ol style="list-style-type: none"> 1. $K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}$ 2. $\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$ 3. $P_k = (I - K_k H)P_k^-$

From Table (1), it is observed that, it computes the state, x and covariance estimates and then forwards them from the time k-1 to k. Q is the process noise.

From the Table (2), the Kalman gain, K_k is computed. Then, in the next step the process is measured to gain z_k , generating a posteriori estimate. R is the measurement noise. This process occurs recursively until a precise measurement the estimates is obtained, and the noise is minimized.

2.2 EXTENDED KALMAN FILTER

The Kalman filter addresses the general problem of state estimation governed by a linear difference equation ^[16]. But in the real-world scenarios, every system comes with a non-linearity. Therefore, a filter which addresses the issue of non-linearity must be used. Hence, the Extended Kalman Filter (EKF), which linearizes about the current mean and the covariance has been introduced by R.E. Kalman. ^[16]

Assuming the process being governed by non-linear stochastic equations is as given below,

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \dots \dots \dots (4)$$

The measurement equation,

$$z_k = h(x_k, v_k) \dots \dots \dots (5)$$

The w_k and v_k are the process noise and measurement noise. X_{k-1} being the previous state estimate at step k-1 and x_k being the current estimate.

Like the Kalman Filter, the EKF also works by predictor-corrector algorithm. The time update being the predictor method and the measurement update being the corrector method. The equations employed in the algorithm are given in the tables (3) and (4) below,

Table 3: Predictor equations for EKF^{[5][16]}

TIME UPDATE(PREDICT)
<ol style="list-style-type: none"> 1. $\hat{x}_{k-} = f(\hat{x}_{k-1}, u_{k-1}, 0)$ 2. $P_{k-} = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T$

Table 4: Corrector equations for EKF^{[5][16]}

MEASUREMENT UPDATE(CORRECT)
<ol style="list-style-type: none"> 1. $K_k = P_k^- H_k^T (H_k P_k^- H_k^T + V_k R_k V_k^T)^{-1}$ 2. $\hat{x}_k = \hat{x}_k^- + K_k (z_k - h(\hat{x}_k^-, 0))$ 3. $P_k = (I - K_k H_k) P_k^-$

The Jacobian matrices A and W are represented with respect to x and w at the interval step k as below,^[16]

$$A_{[i,j]} = \frac{\partial f[i]}{\partial x[j]} (\hat{x}_{k-1}, u_{k-1}, 0) \dots \dots \dots (6)$$

$$W_{[i,j]} = \frac{\partial f[i]}{\partial w[j]}(\hat{x}_{k-1}, u_{k-1}, 0) \dots \dots \dots (7)$$

Where A_k and W_k are the process Jacobian matrices at step k and Q_k is the process noise covariance and R_k is the measurement noise covariance. Jacobian matrix H_k is an important feature in the EKF as it helps the Kalman gain to correctly propagate the necessary parameter of the measurement equations.

3.METHODOLOGY

This chapter discusses about the theoretical applications and then verified by the simulation in the MATLAB/Simulink software. The PV module is simulated along with a DC-DC converter and with two different filters under normal conditions and partially shaded conditions.

Firstly, the PV module with DC-DC converter is simulated with the Kalman filter under normal and shaded conditions. Then, it is simulated with the extended Kalman filter under normal and shaded conditions and both are compared to verify the performance and efficiency of the tracking response of the maximum power in both the filter cases.

The general block diagram for the maximum power-point tracking of a solar panel with a DC-DC converter is as shown in the fig. (8),

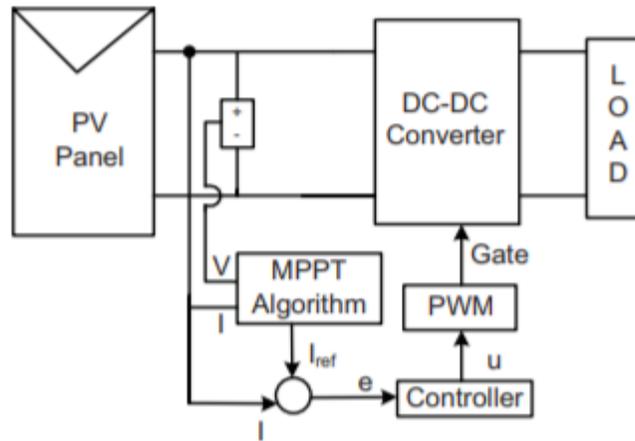


Figure 8: Block model of the MPPT of the Solar module ^[21]

By providing a suitable duty cycle for the MPPT algorithm to identify the maximum power point and make the solar panel to utilize that power efficiently.

3.1 PV MODEL DESIGN

This section discusses about the design of the solar panel module with the photovoltaic cells as mentioned in the above chapter 2. The electrical design and the mathematical equations which are formulated for the design fig. (9) is mentioned below.

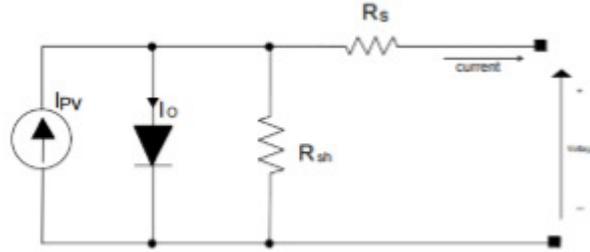


Figure 9: Equivalent circuit of Solar cell^[1]

The current source for the above circuit is I_L , series and parallel resistances R_s and R_{sh} .

The output current, I is calculated as ^[5],

$$I = I_{pv} \left\{ \lambda - \frac{1}{\frac{qA}{eKT}} \left(e^{\frac{qAV}{KT V_{oc}}} - 1 \right) \right\} \dots \dots \dots (8)$$

Here, V_{oc} represents the open-circuit voltage,

I_{pv} denotes the source current which varies with each time step,

The irradiation, λ is 1 kW/m^2 ,

Temperature, T is 25°C ,

q represents the charge of the electron = 1.6×10^{-19} ,

K denotes the Boltzmann constant = 1.38×10^{-23} ,

A is the surface area which is a constant usually taken as 0.2464 .

V and I are the output voltage and current of the solar array.

3.2 MAXIMUM POWER-POINT TRACKING USING KALMAN FILTER

The Kalman filter has many applications as in GPS, navigation, television sets, satellite communication receivers and so on. The algorithm used by the Kalman filter is a set of mathematical equations which have high accuracy in estimating the states of the system using the outputs from the feedback of previous estimations in a recursive manner.

When the MPPT performance of the Kalman filter was compared to that of the most widely used perturb and observe algorithm, the tracking response of the Kalman filter was found to be much faster than that of the P&O.

The flow of the algorithm for the Kalman Filter tracking of the maximum power-point (MPP) is as shown in the fig. (10) below,

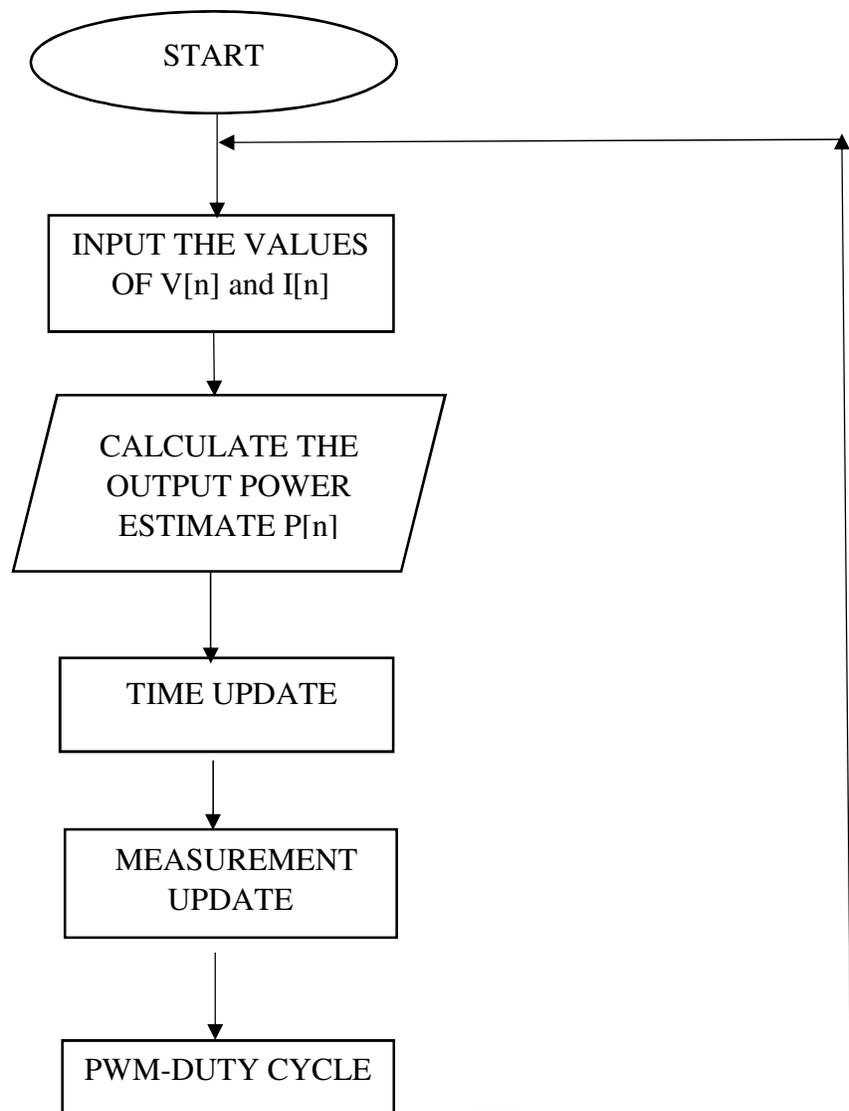


Figure 10: Flowchart illustrating the functioning of Kalman Filter ^{[15][12]}

The PV module is given a voltage and power as the inputs initially, with which the system calculates the output power and the rate of change of current and voltage with respect to each time step. Then, the output current and voltage at each time step is feedback as input to the solar panel at every iteration.

For the tracking of maximum power-point (MPP) with the Kalman filter, the system is represented by the following set of stochastic equations^[5],

$$V_{act}[n + 1] = V_{act}[n] + M \frac{\Delta P}{\Delta V} \dots\dots\dots (9)$$

From the equation (), the above equation was derived where, $V_{act}[n+1]$ represents the estimation of the new state at the step $n+1$ from that of the previous estimation $V_{act}[n]$. M denotes the corrector constant for the step-size and $\frac{\Delta P}{\Delta V}$ represents the slope of the P-V characteristic which is similar to the control input $u[n]$ at time n . And the matrices A is equal to 1 and B is equal to M in the above equation ().

The measurement equation is written with respect to the value z_k in the equation (10)^[5],

$$y[n] = V_{act}[n] + v \dots\dots\dots (10)$$

Where the matrix C is 1 and v is the measurement noise and $y[n]$ being the reference at the time interval n .

The predictor-corrector algorithm for the Kalman filter PV module is written as follows,

3.2.1 TIME UPDATE

The predictor step or the time update method takes place in two steps as given by the following equations in the table (5),

Table 5: Predictor equations for MPPT using Kalman Filter^[5]

TIME UPDATE(PREDICT)
1. $V_{act}^{n-} = V_{act}^{n-1} + M \frac{\Delta P_{n-1}}{\Delta V_{n-1}}$
2. $z_{n-} = z_{n-1} + Q$

The first step in time update represents the projection of the state estimate ahead and the second step denotes the forwarding of the error covariance ahead.

3.2.2 MEASUREMENT UPDATE

The corrector step or the measurement update method utilizes three steps to obtain the accuracy as shown in the table (6) below,

Table 6: Corrector equation for MPPT using Kalman Filter^[5]

MEASUREMENT UPDATE(CORRECT)
<ol style="list-style-type: none">1. $K = z_n^-(z_n^- + R)^-$2. $V_{act} = V_{act}^- + K(V_{ref} - V_{act}^-)$3. $z_n = (1 - K)z_n^-$

The first step involves the computation of the value of the Kalman gain and second step involves the estimation of the state dependent on the measurement value z_k . Thirdly, the accurate error covariance is estimated. These outputs are feedback as inputs to the time update method and this process takes place continuously until the precise estimation is obtained.

With the above equations, the simulation model was designed for the maximum power-point tracking with the DC-DC converter in the MATLAB/Simulink as follows under normal conditions as given in the fig. (11) below,

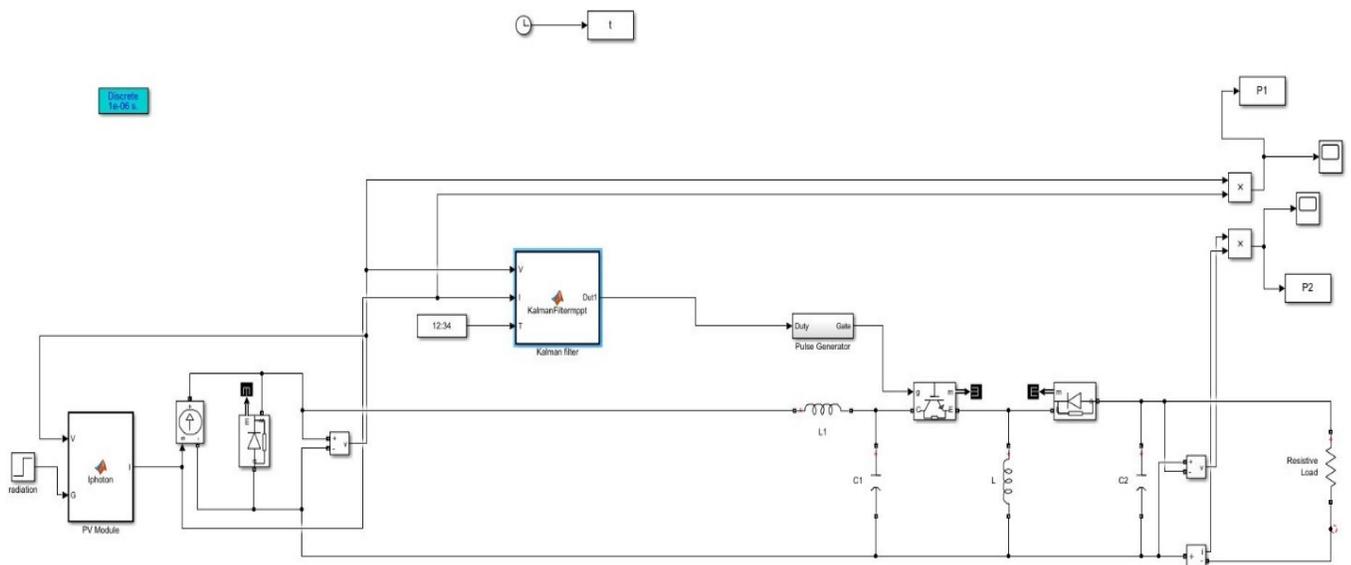


Figure 11: Simulink Model for MPPT using Kalman Filter^[15]

3.3 MAXIMUM POWER-POINT TRACKING USING EKF

Basically, a dynamic system is available with several uncertainties on certain parameters of the model^[1]. Therefore, several measurement points are taken into consideration and hence, Kalman filter is suitable for such process.

However, the characteristics of the PV module shows that the output power always has some non-linearity with respect to the constantly changing parameters such as irradiance, temperature, voltage and so on.

Considering the non-linearity, the Extended Kalman Filter is best suitable and fast for the tracking in real time. It estimates the system's state from the previous value of the state model and minimizes the quadratic error. The general model of functioning of the EKF is as shown in the fig. (12),

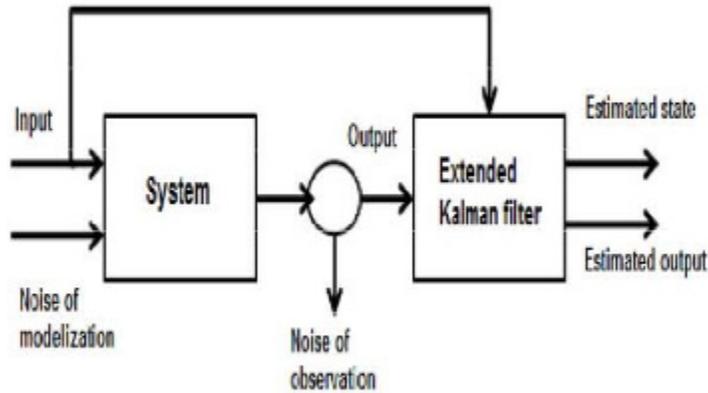


Figure 12:Block diagram for EKF^{[1][5]}

The extended Kalman filter is just a modified version of the Kalman filter but unlike it, the EKF stands out on the point of linearity. The non-linearity is linked with the process or observation.

Based on the equations (), written in the section 2, the state equation and observation equation are written as given below,

Assuming the state equation to be linear here ^[1],

$$S_t = AS_{t-1} + q_t \dots\dots\dots (11)$$

Where S_t is the current state estimate,

A is the matrix with respect to the previous state estimate, S_{t-1} ,

q_t is the gaussian noise noting to the covariance matrix of noise, Q .

The observation equation is modified as follows,

$$C_t = h_t(S_t) + r_t \dots\dots\dots (12)$$

C_t is the observation measure at the time, t

R_t is the gaussian noise centered by the noise covariance, R .

The EKF algorithm also utilizes the predictor-corrector method and the MPPT and estimation equations are given on the following section.

3.3.1 TIME UPDATE

The time update (or) predictor equations are written in two steps similar to the Kalman filter equations as shown in the table (7),

Table 7: Time update equations for MPPT using EKF^{[1][5][16]}

TIME UPDATE(PREDICT)
<ol style="list-style-type: none"> 1. $V_{act}^{n+1} = V_{act}^n + M \frac{\Delta P_n}{\Delta V_n} + w$ 2. $z_{n-} = z_{n-1} + Q$

Where the jacobian matrix A is assumed to be equal to 1 and the matrix B is equal to M, which is the corrector step size. $\frac{\Delta P_n}{\Delta V_n}$ denotes the slope of the power curve. Ct is the reference power, leading to a state estimation with

$$V_{ref}^t - V_{act}^t = v \dots \dots (13)$$

Q denotes the noise covariance of the process.

3.3.2 MEASUREMENT UPDATE

Like Kalman filter, the filter equations are written in three steps but with non-linear function dependent on the estimate at time, t is written as shown in the table (8),

Table 8: Measurement update for MPPT using EKF^{[1][5][16]}

MEASUREMENT UPDATE(CORRECT)
<ol style="list-style-type: none"> 1. $K_n = z_{n-1}(z_{n-1} + R)^{-1}$ 2. $V_{act}^n = V_{act}^{n-} + K_n (V_{ref}^n - h_n(V_{act}^{n-}))$ 3. $z_n = (1 - K_n)P_{n-1}$

The first step depicts the computation of the Kalman gain at the time step, n . The second step is the estimation of the state with the help of the Kalman gain and the most important feature, h_n which is the non-linear function which helps magnify the precise estimation of the process. Thirdly, the prediction of the covariance noise is done.

Then, the output of the corrector technique is feedback to the time update as the input at each step of time as the process occurs recursively until the precise and desirable output estimate is produced.

These equations are implemented in the MATLAB/Simulink simulation model of the solar panel with DC-DC converter and extended Kalman filter algorithm to obtain and track the maximum power-point is as shown in the fig. (13),

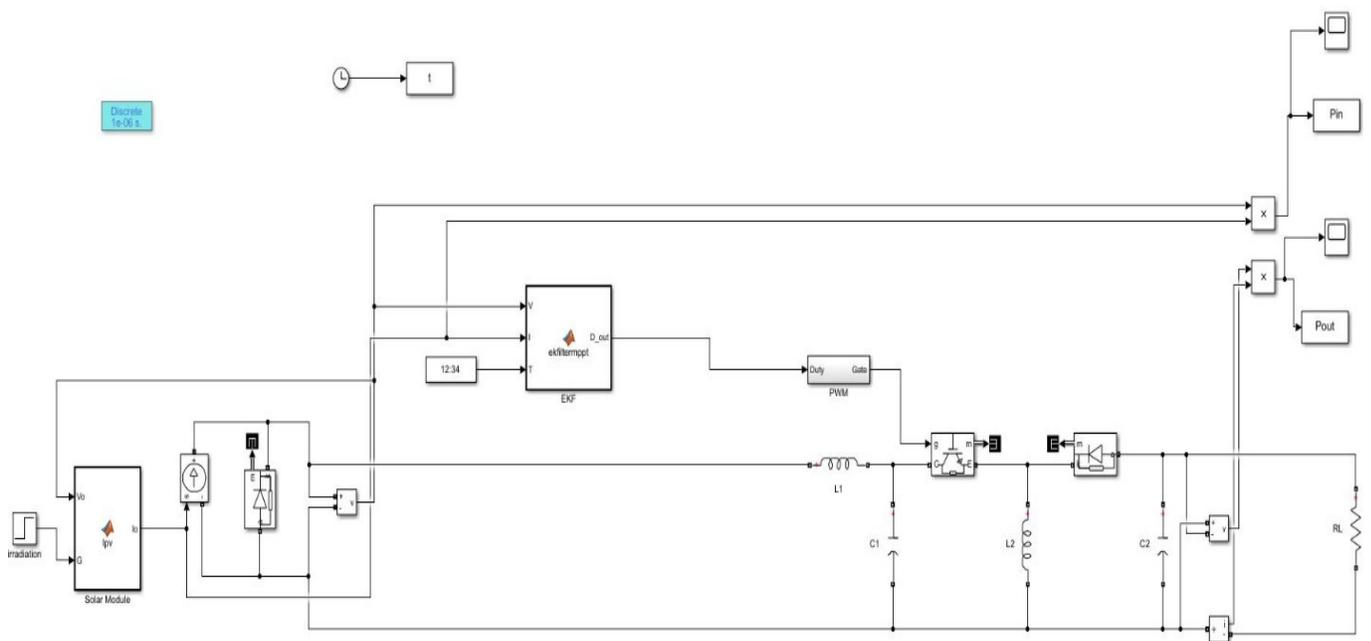


Figure 13: Simulink model for MPPT using EKF under uniform irradiation [15]

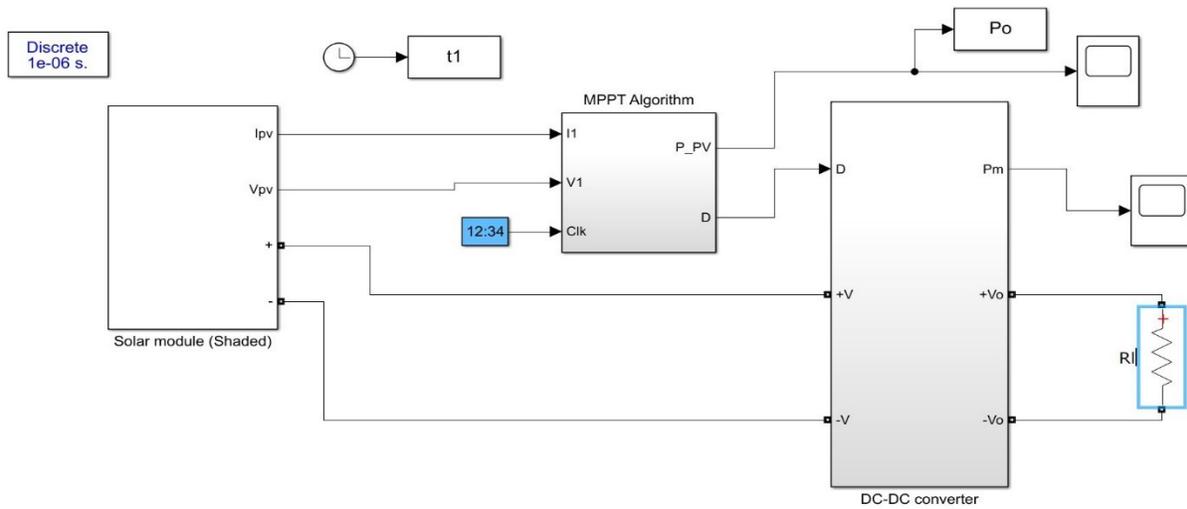


Figure 14: Simulink model for MPPT using Extended Kalman filter under shaded condition^[22]

Fig. (14) shows the Simulink model embedded with MPPT algorithm of Extended Kalman Filter under the partial shading condition with constantly changing voltage or irradiance.

4.SIMULATION RESULTS

From the above chapter, the MATLAB/Simulink models were simulated with different techniques and algorithms. This chapter explains the output obtained by the models with Kalman filter and Extended Kalman Filter under normal and partially shaded conditions.

4.1 OUTPUT FOR THE KALMAN FILTER UNDER NORMAL CONDITIONS

The fig. (15) shows the output power of the solar module with the Kalman filter algorithm under normal conditions, plotted power in watts versus time in seconds.

The curve starts at zero watts at zero seconds and gradually increases to 27 watts to 30 watts then, becoming constant. The curve tends to have some noises which shows its disadvantage of not rectifying the non-linearity in the system. The power raises to the maximum power-point at the time of 2.5 seconds. Here, a uniform irradiation of 1000 kW/m^2 at a temperature of 25°C [15][5][1].

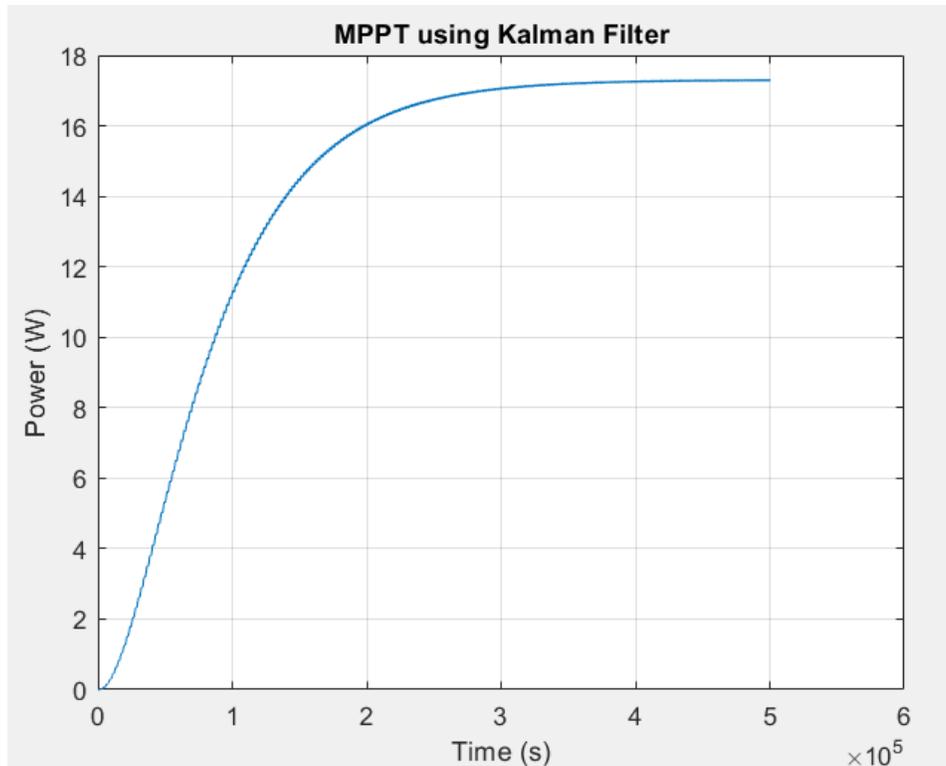


Figure 15: Convergence of power with time under uniform condition

4.2 OUTPUT FOR THE KALMAN FILTER UNDER SHADING CONDITIONS

Then the simulation is done under partial shading conditions, where the solar cells are shaded with different irradiant levels like 1000, 800, 300, 100 kW/m² [5][1][15][16] and the temperature at 25°C. The fig. (16) shows the power characteristic curve, which under shaded environment produces various peaks or power points where one is considered the global power-point (GPP) and the other peaks local power-points (LPP).

From the plot (16) shown below, due to the shading effects and the simulation being run for 6e(5) seconds, there occurred two local power points and one global power point (GPP) at 400 watts.

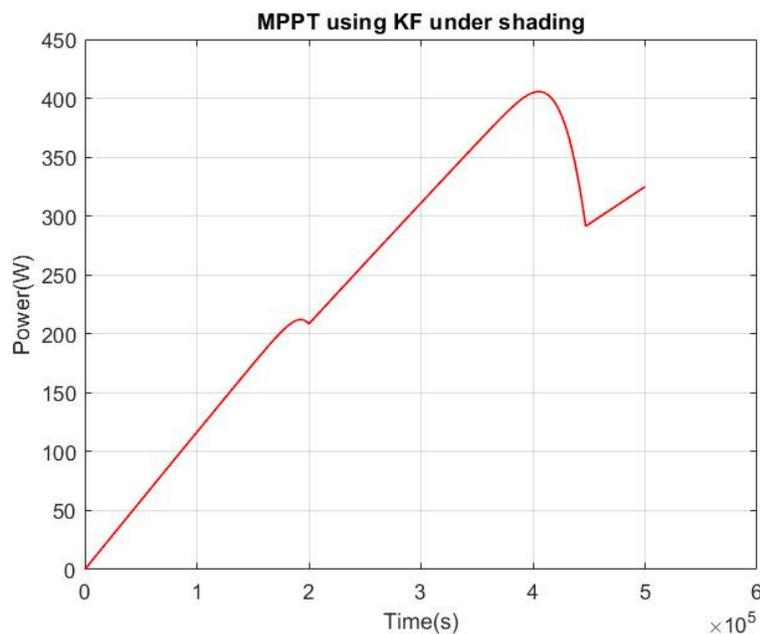


Figure 16: Power characteristics of solar cell under shading

4.3 OUTPUT FOR THE EXTENDED KALMAN FILTER UNDER NORMAL CONDITIONS

The solar module with extended Kalman filter algorithm is simulated with a uniform irradiation of 1000 kW/m^2 [1][5][15] and fed through a DC-DC converter. The convergence of power with respect to the time in seconds is as shown in the fig. (17) below,

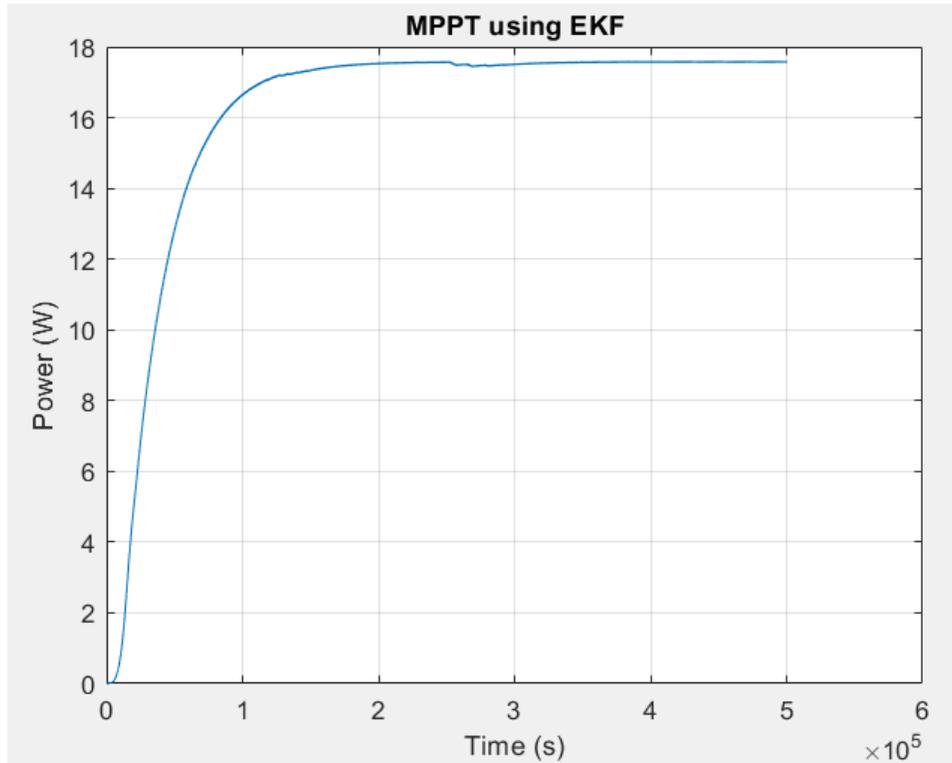


Figure 17: Power convergence curve of EKF under uniform conditions

It is seen that the power starts at zero watts and starts gradually increasing at 0.1 second till 1 second where it reaches the maximum power of about 17.8 watts and then remains uniform throughout.

4.4 OUTPUT FOR THE EXTENDED KALMAN FILTER UNDER PARTIALLY SHADED CONDITIONS

Like the condition for the Kalman filter algorithm used for the solar module, the extended Kalman algorithm also uses different irradiation levels as input to the photovoltaic panel. The irradiation level given to the model are 1000, 800, 300 and 100 kW/m^2 . [1][5][15][11]

The fig. (18) denotes the plot of maximum power point curve of the solar module with extended Kalman filter algorithm under the partially shaded condition. Under the shaded circumstances, the PV panel shows multiple peaks of local power points and one global power point. The extended Kalman filter is believed to have minimized the error and works efficiently with non-linearities.^{[1][15][5]} The global power point was found to be at the 415 watts at the time 4.2 seconds.

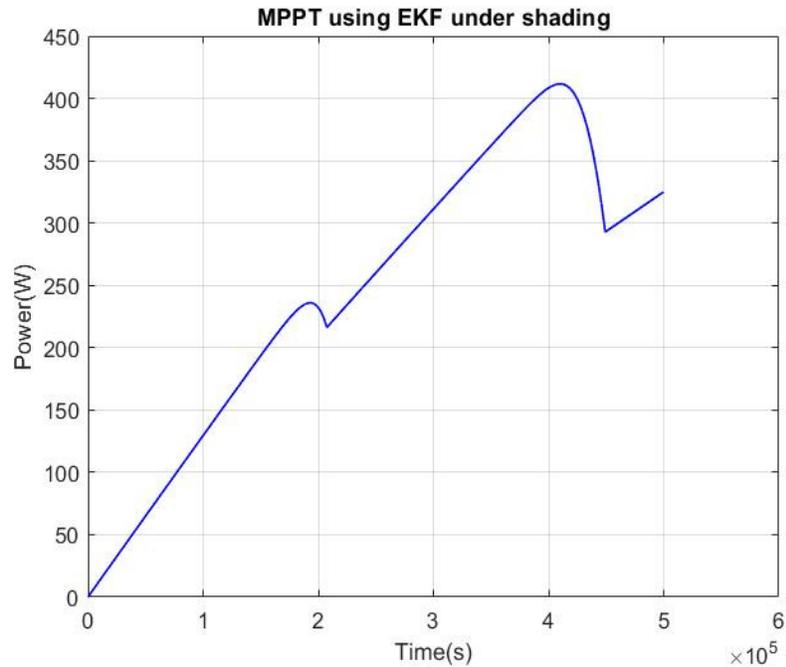


Figure 18: MPPT under partial shading using EKF

5. ANALYSIS AND DISCUSSION OF THE RESULTS

5.1 PERFORMANCE OF MPPT ALGORITHM

After simulating the photovoltaic models under normal and partially shaded conditions, the output power curves obtained with the Kalman Filter algorithm and the extended Kalman filter algorithm are compared and analyzed to find out which suits better for certain conditions.

5.2 UNDER UNIFORM CONDITIONS

From the previous chapters, it can be seen that the maximum power-point is a method to obtain an optimum voltage to run the system efficiently. On simulating the photovoltaic panel under a uniform environment where the irradiations are given as a uniform input with a value of 1000 kW/m^2 at the temperature of 25 degree Celsius, the power curve is obtained^{[1][15][11][5]}.

The output power convergence plots obtained from the maximum power-point tracking using the algorithms of the Kalman Filter and the Extended Kalman Filter are compared. On analyzing the plot as shown in the fig. (19), it is seen that the Extended Kalman Filter has a much faster tracking response as the power curve starts at 0.1 second and increases gradually to the maximum power of 17.8 watts at 0.78 seconds.

Whereas, with the Kalman Filter algorithm, the tracking response is delayed at 0.2 seconds and reaches the maximum power of 17 watts at one second. It is also seen that the output is affected by some noise parameters due to the non-linearity of the system. The maximum power obtained at each situation are tabulated in the table (9) below,

Table 9: Performance analysis under uniform conditions

	KALMAN FILTER	EXTENDED KALMAN FILTER
Tracking response ($\times 10^5$ seconds)	1 second	0.78 second
Maximum power	17 watts	17.8 watts

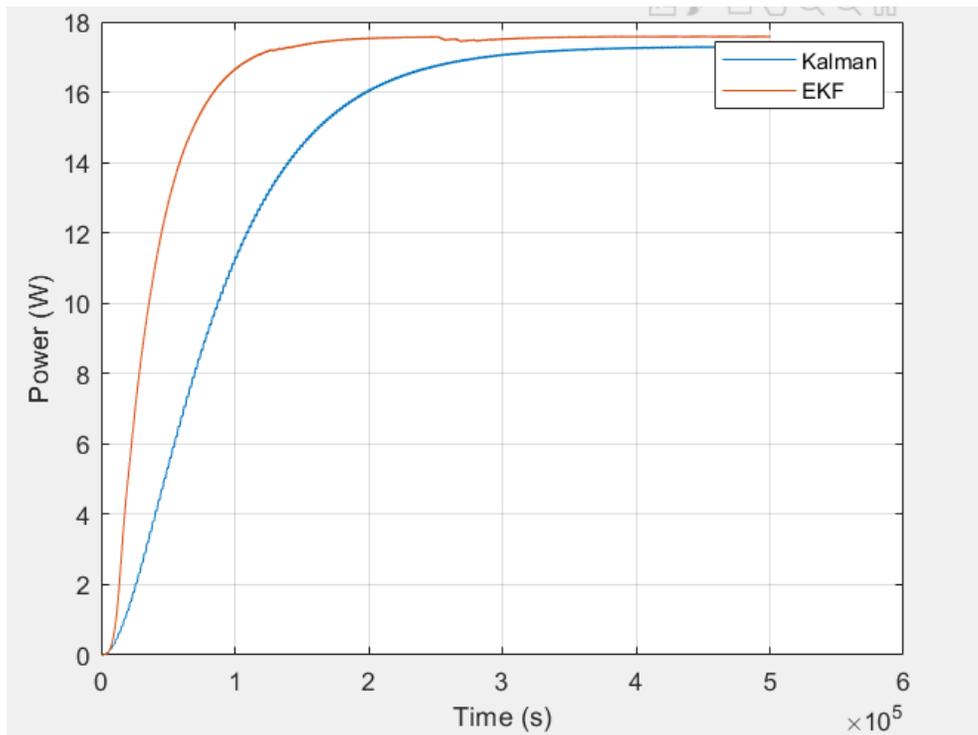


Figure 19: Comparison of power convergence curve of KF and EKF

5.3 UNDER PARTIALLY SHADED CONDITIONS

After analyzing the solar module under uniform conditions, the module was tested with non-uniform irradiation conditions also known as partially shaded conditions. The model was simulated with the inputs of irradiances 1000, 800, 300 and 100 kW/m² at the temperature of 25 degree Celsius.

The power convergence plots obtained from that of the Kalman filter and EKF algorithms are compared and analyzed for their performances as shown in the fig. (20). The Extended Kalman filter had its maximum power point at 415 watts at 4.1 seconds and the Kalman filter gained the MPP at 400 watts at 4.1 seconds is shown in the table (10),

Table 10: Performance analysis under partial shading

	KALMAN FILTER	EXTENDED KALMAN FILTER
Tracking response (x10 ⁵ seconds)	4.1 second	4.1 second
Maximum power	400 watts	410 watts

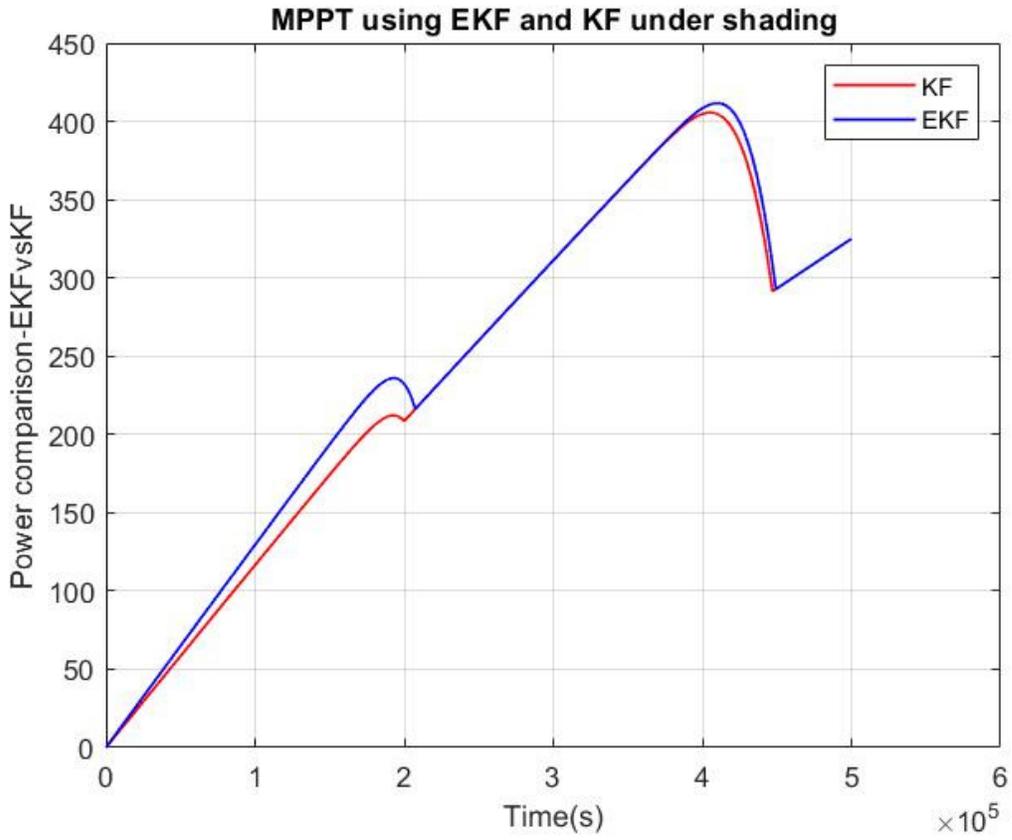


Figure 20: Comparison of power curves under partial shading

6.CONCLUSION

In this research, the study of the photovoltaic module operated by maximum power-point tracking techniques with the help of Extended Kalman Filter (EKF) is compared to that of the Kalman Filter under uniform conditions and partially shaded conditions. The Kalman filter basically is modelled by a set of linear differential stochastic equations and is used to estimate the state of the system and minimize the mean-squared error ^{[16][1]}.

While in the real-life dynamics, no system is linear. Every system or process is built with a non-linearity(s) so, the Kalman Filter is not suitable for tracking the power at noisy and constantly changing environment. Hence, EKF is introduced to deal with this situation and it is also recursive in nature. The computation of the jacobian matrices help in dealing with the constant changes in the system^[16].

From the experiment done in this research, the performances of the MPP algorithm used by the EKF is compared with that of the Kalman filter. It is found that the extended Kalman filter model has much faster tracking rate and precise estimation of the power compared to that of the Kalman. The efficiency of the extended Kalman filter is about 99.7 % and having a faster response of tracking the power both under normal and the partially shaded conditions. Hence, proving that the EKF is the best suitable and more efficient technique for finding the optimum power of the system even if the dynamics of the system is unknown ^[16].

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APPENDIX

MATLAB CODE FOR MPPT USING KALMAN FILTER

```
%Time Update
V_hat = V_hat+M*(dpdv);      %Matrices A=1 and B=M

H = H+Q;                    %H=error covariance, Q=process
                             Noise covairance

%Measurement Update

K = H/(H+R);                % K=Kalman gain, R=measurement
                             Noise covariance
z = V+v;                    % z=reference voltage
V_hat = V_hat+K*(z-V_hat);
H = (1-K)*H;
```

MATLAB CODE FOR MPPT USING EXTENDED KALMAN FILTER

```
%Time Update
Vhat = Vhat+M*Isc*(Ir-
(1/exp(c)*((c/Voc)*exp((c*Vhat)/Voc)+exp((c*Vhat)/Voc)-
1)));                        % Jacobian Matrix A=1,
B=M*Isc*(Ir..) %

H = H+Q;

%Measurement Update
Vtilde=Vhat+w;
K = H/(H+R);
z = V+v;
z1=V;
Vhat = Vhat+K*(z-z1-(Vhat-Vtilde)); %non-linear function
                                     h(x,0)=z1-(Vhat-Vtilde)
H = (1-K)*H;
```