A Kalman filter based MPPT algorithm

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Abstract: The sun is a plenty and popular source of renewable energy. To transform solar energy into electricity it is necessary to use photovoltaic (PV) panels which in turn have low efficiency and therefore do not provide maximum power. Maximum power depends on temperature and solar radiation. Changes in these environmental factors require an algorithm to find the Maximum Power Point (MPP) where maximum power can be extracted. The algorithm is called the Maximum Power Point Tracking (MPPT). Through MatLab/Simulink the MPPT algorithm based on the Kalman Filter was implemented. The MPPT algorithm is essential for the maximum use of solar energy and therefore plays an important role for the feasibility and competitiveness of PVs in renewable energy. This article proposes a MPPT based on the kalman filter that has the advantage of efficiently estimating variables based on measurements with statistical noise, in this case measurements of solar irradiation and temperature. The results show efficiency because the relative errors are less than 1.13% compared to results obtained from simulink.

Keywords: Photovoltaic panel; maximum power; tracking algorithm; MPPT; Kalman filter

1. INTRODUCTION

Global warming and consequent climate change are requiring the replacement of fossil fuels with renewable energy. These energies are those related to natural sources and which can be reused such as wind and solar energy (Pali and Vadhera (2016)).

Due to the fact that the planet earth receives energy from the sun, around 1.5×10^{18} kWh, which corresponds to 1000 times the amount of energy consumption in this period of time, makes solar energy one of the most popular among renewables. To convert the solar energy in the form of electricity, a PV panel is required, that converts light energy into electrical energy. However, a photovoltaic panel itself has low efficiency, and as a consequence, it does not provide maximum power (Wan et al. (2015)).

Maximum power depends on temperature and solar radiation, as a consequence sudden changes in these environmental factors imply the need to include a tracker to find an operating point called MPP from which power is maximized. Power maximization is performed by a power tracker known as Maximum Power Point Tracking (MPPT) that provides the voltage and current values that determine the MPP point (Sen et al. (2017)).

Over time, many algorithms have been developed to find the MPP being the most used: Incremental Conductance, Disturb and Observes, Fuzzy Control and Neural Networks. Despite the good applicability of these algorithms, researchers continue to study and design new algorithms in order to lower costs and achieve satisfactory results in the optimization of Maximum Power as pointed out in Verma et al. (2016).

In the literature, a new trend for such kind of problems, which has been giving good results is the Kalman filter, which is a computational method based on the recursion of least squares methods. The qualities of the filter are associated with the possibility of predicting future states through present and past estimates even in the absence of the system model (Li et al. (2015)).

In this perspective, Ramchandani et al. (2012) designed the Kalman filter to find the MPP, but did not contemplate temperature variation and solar irradiation as well as not measuring the efficiency of the MPPT algorithm.

Therefore, the objective of this paper is to implement the Kalman filter-based MPPT through Matlab/Simulink in the conditions of temperature changes and solar irradiation and to verify the efficiency through the found results .

2. THE PHOTOVOLTAIC PANEL

The union of photovoltaic cells in series and parallel produce a photovoltaic panel. Because cells provide low voltage and current, they are joined in series to increase voltage while joining in parallel is to raise current (Tanemo et al. (2018)).

Fig.2 shows an equivalent circuit of a photovoltaic panel containing a parallel current source with a diode and two resistors (one in series and one in parallel). According to Bilhan et al. (2016), the mathematical representation of a photovoltaic panel can be described by the equations 1, 2 and 3 .

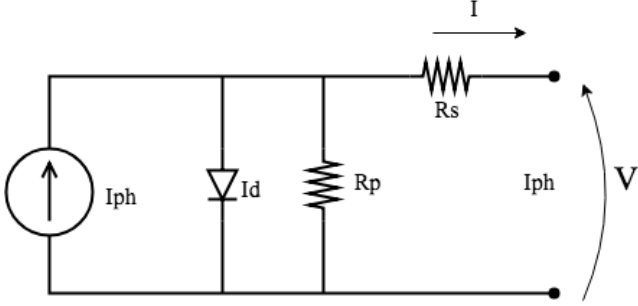$$I = I_{ph} - I_d[e^{\frac{q(V+IR_s)}{nKT}} - 1] - (\frac{V+IR_s}{R_p}) \qquad (1)$$

Figure 1. Equivalent circuit of a traditional photovoltaic cell

$$I_{ph} = [I_{sc} + \alpha(T - T_r)]\frac{\lambda}{1000} \quad (2)$$

$$I_d = I_{rr}(\frac{T}{T_r})^3 e^{[\frac{qE_g}{nK}(\frac{1}{T} - \frac{1}{T_r})]} \quad (3)$$

Where: I is the output current of the photovoltaic panel; I_{ph} the photo current; I_d the reverse saturation current of the cell; n the join quality factor p-n; V a Cell output voltage; q the electron charge $1.6 \times 10^{-19}C$; K the Boltzman constant ($1.38 \times 10^{-23}J/K$); R_s the series resistance; R_p the parallel resistance; I_{sc} the short circuit current; α the temperature coefficient of I_{sc}; T_r the reference temperature of $298K$ (25 °C); λ the solar radiation intensity at W/m^2; E_g the energy of the forbidden band (Durgadevi et al. (2011)).

Table 1 shows the characteristics of the photovoltaic panel model (**MX60 PV**) extracted from Matlab/Simulink, for a solar irradiation and temperature conditions of 1000 W/m^2 and 25 °C respectively.

Table 1. Characteristics of the PV Panel Model MX60

Features	Value
Maximum Power (W)	60.53W
Open Circuit Voltage V_{oc}	21.10 V
Voltage on the MPP V_{mp}	17.04 V
Temperature Coefficient of V_{oc}	-0.22 (%/ deg.C)
Short Circuit Current I_{sc}	3.80 A
Current on the MPP I_{mp}	3.55 A
Temperature Coefficient of I_{sc} (%/ deg.C)	0.03 (%/ deg.C)

Two cases of PV panel were simulated by Matlab/Simulink. In the first case, the PV panel was simulated with a constant temperature of 25 °C and solar radiation variations of 1000 W/m^2, 800 W/m^2, 600 W/m^2 and 500 W/m^2 as seen by the curves I - V and P - V from Figures 2 and 3. In the second case, the PV panel simulation took place with constant solar irradiation of 1000 W/m^2 and temperature variations of 25 °C, 50 °C, 75 °C and 100 °C as noted by the curves I - V and P - V from Figures 4 and 5

By the analysis of Figures 2 and 3 it is clear that the increase of the output current and the power of the PV panel depends on the increase of solar irradiation. While an evaluation of Figures 4 and 5 show that the voltage and output power of the photovoltaic panel decreases as its temperature increases. The implications described here, prevent MPP tracking, requiring therefore a MPPT
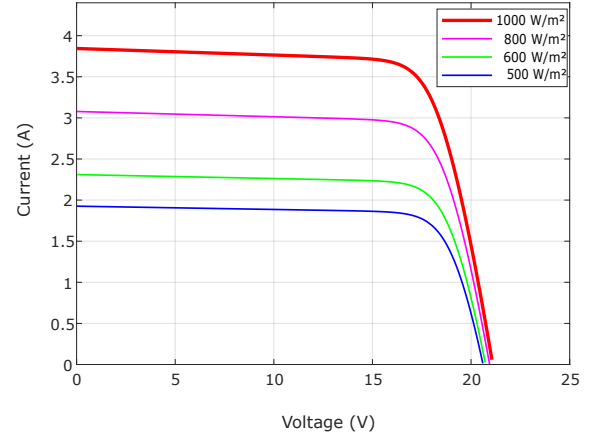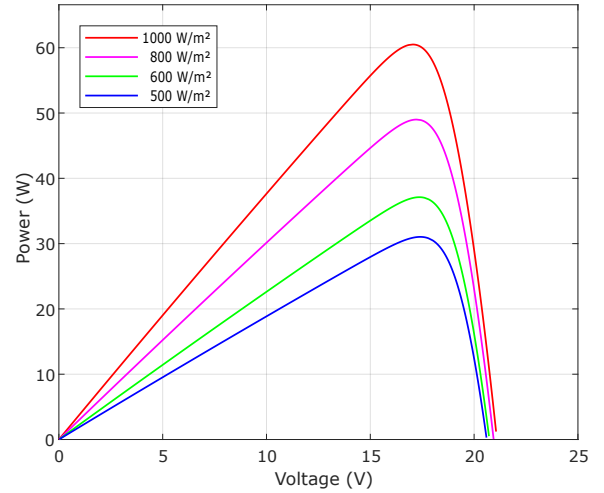

Figure 2. PV $I \times V$ curve
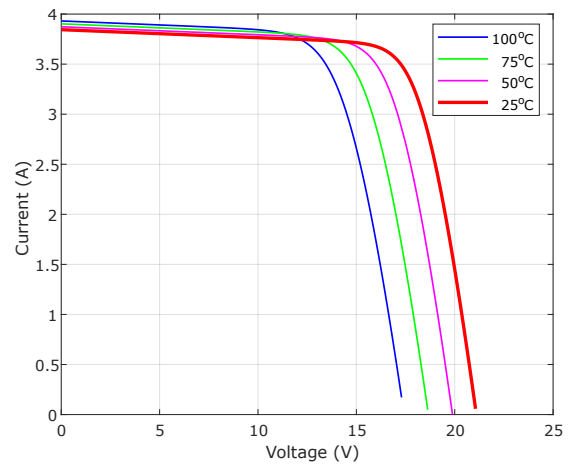

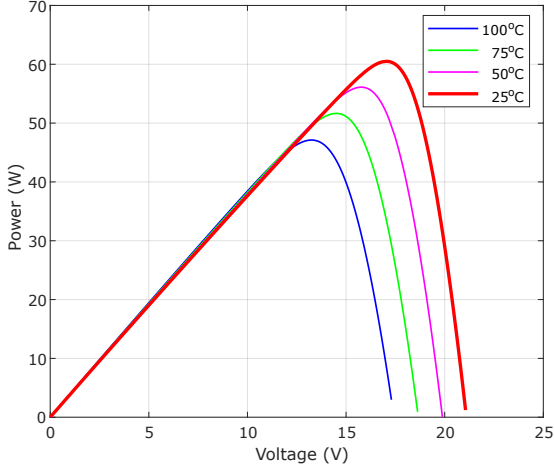Figure 3. PV $P \times V$ curve

Figure 4. PV $I \times V$ curve

Figure 5. PV $P \times V$ curve

algorithm tracker for power maximization (Peng et al. (2018)).

3. MPPT ALGORITHM

Since the curves of Fig. 2, 3, 4 and 5 are modified with variation in temperature and solar irradiation, it is necessary an algorithm to find the MPP when these variations occur. A way to find the MPP in a PV panel is using a MPPT algorithm as Fig. 6 (Han and Jia (2012)).
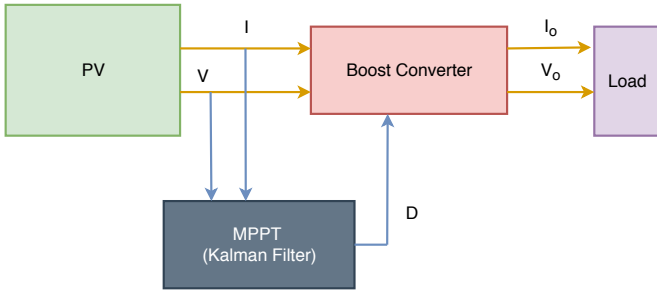

Figure 6. PV system scheme

Fig. 6 shows the architecture of a PV system. As can be seen, the Boost converter is controlled by the MPPT algorithm and positioned between the PV panel and the load (Ibrahim et al. (2015)).

3.1 Boost Converter

The Boost converter, when operating in continuous mode, converts the DC voltage (V) into another DC voltage (V_o). This converter, as seen in Fig. 7 contains a MOSFET that is controlled by a Pulse Width Modulation (PWM). The other electrical components have a distinct function that will depend on the state (on or off) of the switch. When the switch is on, the inductor stores power from the PV panel, while the diode turn off the PV output, and the output capacitor provides current to the load. However, in the situation where the switch is off, the inductor is in discharge mode and the diode polarizes and connects the output of the PV panel. As a consequence of the on and off state of the switch, the output voltage (V_o) is always greater than the input voltage (V), since it is the sum of the input and the inductor voltage (at discharge) (Hasaneen and Mohammed (2008)).
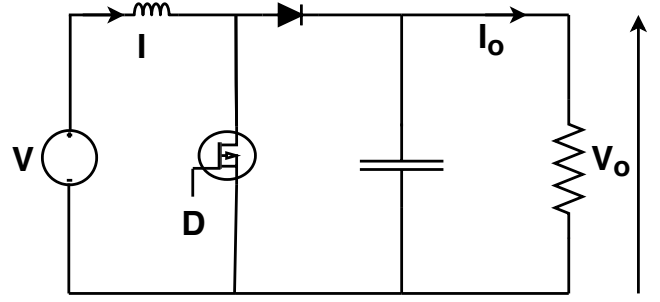

Figure 7. Boost Converter

The equations of the Boost Converter are:

$$V_o = \frac{V}{1 - D} \qquad (4)$$

$$I_o = I(1 - D) \qquad (5)$$

Where: I is the PV panel current (input), I_o is the system output current and D is the duty cicle. Analysis of 4 allows us to deduce that the value of D depends on the value of V, this means that changes in the voltage value reach the duty cicle value (Rakhmawati et al. (2017)).

3.2 The Kalman Filter

Formulated by Rudolph Kalman in 1960, the Kalman filter consists on equations that recursively provide a solution for the least squares method. The Kalman Filter is very popular because of the good results presented in various areas of knowledge. The use of the Kalman Filter is due to the prediction of a future state, even in the absence of a mathematical model, by means of present and past estimates. Estimates in the Kalman Filter are performed by combining two steps: *prediction* and *correction*. Each step has its own sets of equations. The equation 6 is the first equation of the *prediction* step and serves to project the next state (Li et al. (2015), Costa et al. (2005), Kang and Park (2011)).

$$x_k^- = Ax_{k-1} + Bu_{k-1} \qquad (6)$$

Where: x_k^- is the estimated state in the predicted iteration k from the previous iteration. x_{k-1} the rectified state in the iteration $k-1$ found by the output measure z_{k-1}. u_{k-1} is the control process of the $k-1$ iteration process. A is the transition state constant model used for the previous state. B a constant that depends on the model that is used in the control process (Costa et al. (2005)). The second equation of the prediction step is used to project the next covariance error.

$$H_k^- = AH_{k-1}A^T + Q \qquad (7)$$

Where: Q is the covariance process related to the noise state matrix. H_k^- the covariance *a priori* for the k iteration. H_{k-1} the covariance error a *posteriori* for iteration

$k + 1$ (Costa et al. (2005)). The second step (*correction*) aims to correct the value predicted by the *prediction* step. The first equation of this step calculates the K gain.

$$K_k = H_k^- C^T (C H_k^- C^T + R)^{-1} \qquad (8)$$

Next, the estimate x_k is updated via output z_k.

$$x_k = x_k^- + K_k(z_k - C x_k^-) \qquad (9)$$

And finally the last equation that updates the covariance error.

$$H_k = (I - H_k C) H_k^- \qquad (10)$$

Where: x_k is the corrected state at iteration k due to z_k output. H_k the covariance of the error a *posteriori* in the iteration k. K_k the Kalman gain. R Covariance of noise. z_k the measurement. C a constant related to the Kalman Filter system and the observed space (Costa et al. (2005)).

3.3 MPPT by Kalman Filter

To find the MPP operating point using the Kalman Filter it is necessary to design the filter to find the maximum power voltage. It can be seen from the curves P - V from Fig. 3 and 5 that the power is increased with a positive slope to the best point and decays with a negative slope. Thus, through these analyzes, we can write equations to predict the MPP stress. As Kang and Park (2011) considers $A = 1$ and $B = M$, so the equations of the *prediction* step are:

$$V_k^- = V_{k-1} + M \frac{\Delta P}{\Delta V} \qquad (11)$$

$$H_k^- = H_{k-1} + Q \qquad (12)$$

Where: V_k^- is the estimated voltage value by the MPPT using the Kalman filter in the k iteration and corresponds to x_k^-. M equivalent to B and is considered a scaling factor. $\frac{\Delta P^{k-1}}{\Delta V^{k-1}}$ the slope of the curve P-V in the iteration $k-1$ and equivalent to the control u_{k-1} (Kang and Park (2011)).

The *correction* step process is made it as follows.

According to Kang and Park (2011), the K gain can be calculated adopting $C = 1$ and by the covariance error as refq:09

$$K_k = H_k^- (H_k^- + R)^{-1} \qquad (13)$$

The equations refeq:10 and refeq:11 of the *correction* step corrects the predicted covariance measurement with the PV panel voltage measurement $V_{photovoltaic,k}$ as follows:

$$V_k = V_k^- + K_k \times (V_{photovoltaic,k} - V_k^-) \qquad (14)$$

$$H_k = (1 - K_k) \times H_k^- \qquad (15)$$

Where: V_k is the value of the corrected voltage using the Kalman filter based MPPT in the k iteration provided by the $V_{photovoltaic,k}$ PV voltage measurement (Kang and Park (2011)).

In Fig. 8 we present the simulation performed by the MatLab/Simulink software, this one presents a PV panel connected with a Boost converter and the MPPT based on the Kalman filter.
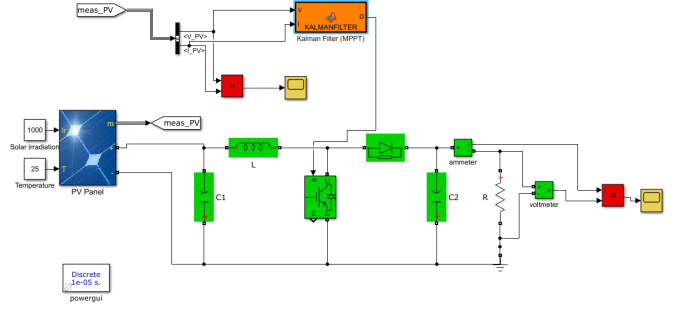

Figure 8. Implementação do MPPT baseado no filtro Kalman usando o software MatLab/Simulink

4. RESULTS

To test the efficiency of MPPT using Kalman Filter, it was simulated two scenarios. In the first scenario, the temperature was maintained at 25 °C and the solar irradiation was varied from 1000 W/m^2, 800 W/m^2, 600 W/m and 500 W/m^2 for 2 seconds. The result of the maximum power found on these implications is shown in Fig. 9. In the second scenario, solar irradiation was kept
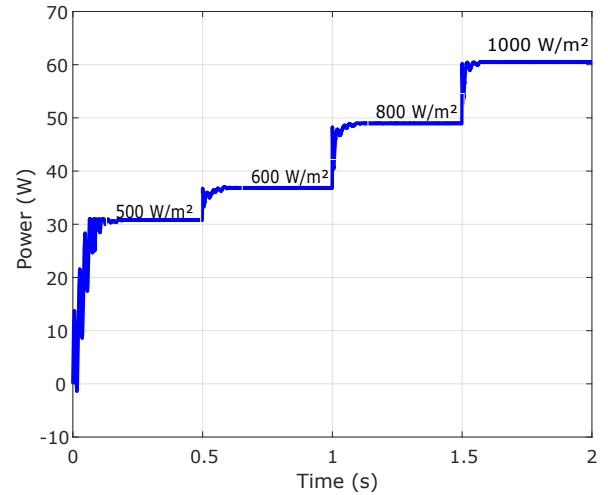

Figure 9. Potência de saída com o algoritmo MPPT baseado no Filtro de Kalma a temperatura constante de 25 °C

constant at 1000 W/m^2 while the temperature is varied at 25 °C, 50 ° C, 75° C and 100 °C for 2 seconds. Figure 10 shows the consequent result.

To measure the effectiveness of MPPT, the values obtained using the above mentioned kalman filter based MPPT were compared with the values provided by Matlab/Simulink of the PV panel. In Table 2 and 3.

According Farayola et al. (2017), among the MPPT algorithms such as Incremental Conductance, Disturb and Observes, Fuzzy Control and Neural Networks, the first has the best efficiency. Dolara et al. (2018) found that the efficiency of Incremental Conductance was 97.4%. Thus, comparing the Incremental Conductance with MPPT Kalman Filter based, the latter is more efficient when it comes to delivering maximum power with a relative error less than 1.13%.
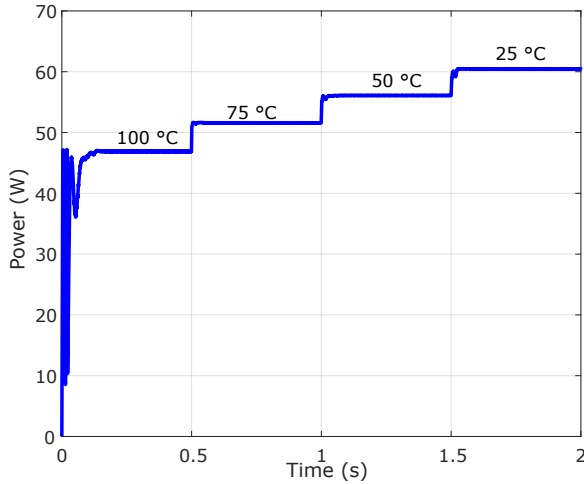
Figure 10. Potência de saída com o algoritmo MPPT baseado no Filtro de Kalman a irradiação solar de 1000 W/m^2

Table 2. Comparison of the output power of the PV panel and the values obtained by means of the algorithm MPPT Kalman filter at constant temperature of 25 °C.

Irradiation W/m^2	Maximum Output Power (W)	Maximum Output MPPT Filter Kalman (W)	Relative error %
1000	60.53	60.45	0.14
800	49.00	48.84	0.13
600	37.11	36.77	0.92
500	31.03	30.84	0.61

Table 3. Comparison of the output power of the PV panel and the values obtained using the algorithm MPPT Kalman filter with a constant solar irradiation of 1000 W/m^2.

Temperature $°C$	Maximum Output Power (W)	Maximum Output MPPT Filter Kalman (W)	Relative error %
25	60.53	60.45	0.14
50	56.74	56.1	1.12
75	51.64	51.62	0.03
100	47.12	46.92	0.42

5. CONCLUSION

By Matlab/Simulink the MPPT algorithm based on the Kalman Filter was implemented in a PV panel with the intention to find the MPP point and thus to extract the maximum power. However, the *I-V* and *P- V* curves of the PV panel change with varying temperature and solar radiation and as a consequence modifies the MPP point, thus the MPPT needs to be designed to find the maximum condition. In this way this paper analyzed two scenarios with changes on environmental factors mentioned here. In the first scenario the temperature was set at 25 °C and the solar radiation varied from 1000 W/m^2, 800 W/m^2, 600 W/m^2 and 500 W/m^2. In the second scenario, the solar irradiation of 1000 W/m^2 was kept constant while the

temperature varied from 25 °C, 50 °C, 75°c and 100 °C. In both scenarios, the Kalman filter-based MPPT algorithm showed efficiency, since the results compared with the Pv panel output power values provided by MatLab/Simulink showed relative errors less than 1.13 %.

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