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A Statistical Approach of Estimating Solar Concentrator for Maximum Power

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Abstract: The objective of this paper is to increase the efficiency of photo voltaic cell and to reduce the cost of the photovoltaic module. The efficiency of photovoltic module isincreased by covering an angle of nearing 180 degree and the costisreduced by use of cheaper glass materials. The amount of currentproduced by a solarcell/panel depends on variousfactors due to which the state variables of a cellkeepchanging. The various state variables in question main festdifferentbehaviours as time and place changes and emprical formula of a solarcelldoes not suffice. In absence of suchemprical formula, one has to relay on estimation in order to predict the behaviour of a solarcell. In thispaperbehaviour of state of solarcell has been done by kalmanfilter. A dynamic rapidmethod for tracking the maximum power angle of solarcellarraysknown as BacteriaForaging Optimisation (BFO) algoritham has been used. Experimentalanalysisispresented for the comparision of different positions of the sun for maximum power alignment.

Keywords: BFO, Concentrators, Kalmanfilter, Photo Voltaic Cell, Solar Panel

1. INTRODUCTION

The photovoltaic modules convert the light energy available from the sun in to electrical energy. It uses the principle that when light strikes a semiconductor material, the photons from the light transfer energy to the electrons of the semiconductor material which generate electricity. So when the number of photons striking the Semiconductor surface of the photovoltaic module is increased the electricity generated is also increased using the same surface area of the photovoltaic module [16].The number of photons striking the surface of the photovoltaic module can be increased by using solar concentrators made of lenses by using the refractive property of the lenses. Also, the design of solar concentrators covers an angle of about 180° in a semi-circular shape. This provides an option of keeping the module fixed at a particular flat position and avoid the rotation of the module in order to face the sun to absorb more sun rays and increase the efficiency.

There are various statistical approaches for estimation of a particular phenomenon, like Bayesian estimator, maximum likelihood estimator (MLE), minimum mean square estimation (MMSE) [9]. Kalman estimator has been found to be more accurate than least squares estimation [20]. Each estimator is optimal for a particular perspective. Our goal is to estimate and predict the state variables of a solar cell in which the noise generated by a photovoltaic cell and the noise of the senor used for current measurement are random in nature. Ours is a time dependent system and best represented by state estimation technique [23].

Although in practice a solar cell has an exponential relationship between its current, incident radiation and temperature, the Kalman filter assumes the system to be linear and we can consider our system to be piecewise linear model. The EKF is a de-facto standard for non-linear systems, but it involves more number of calculations and hence to simplify the approach of estimation it is avoided. Our approach is heuristic in the sense that, sensors on the periphery of a single panel will not correctly measure the dip in output of the adjacent panels which are

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affected by cloud cover asymmetrically. Hence, a single point sensor will not manifest the variability of the whole solar plant.

Efforts has been made by Patnaik et el to accumulate data from different panels connected in WSN (wireless sensor network) and proceed with reconfiguration strategy based on Gauss-Seidel iteration for maximum output power [19]. Satellite based estimation of solar flux is expensive, but it is the only alternative in absence of ground-based data station and proves to be accurate. Various applications of Kalman filter has been found in literature, like, measuring the position of a rotor without position sensor, efficient resource management of data stream to conserve bandwidth while producing maximum throughput to deliver high quality data to the central server, for guiding an autonomous vehicle on the event of GPS failure by fusing data from various sensors. Our work is to estimate and predict the short-circuit current of a solar cell, by using a Kalman filter.

In this paper, we have made an assumption that has been followed by Theocharis et al for linearization of a photovoltaic cell. A piecewise linear model has been deduced by from which we can infer that for small time steps solar radiation intensity is increasing linearly, so as the short-circuit current, that is a direct consequence of solar insolation. The current sensor that is measuring the short-circuit current is a non-linear device. Different non-linear compensation techniques found in several literatures [15] can be used to linearize sensor characteristic. The aforementioned linearization of PV cell generator and the linearization of sensor are assumed, since the focus is on Kalman filter to mitigate the effects of the noise of both the photovoltaic cell and the current sensor for an optimal estimation.

BFO algorithm yields fast and parameter insensitive MPPT of PV systems. BFO is a new algorithm which has simple implementation to track the maximum power point of photovoltaic array or a solar panel. Nowadays Bacteria Foraging technique is gaining importance in the optimization problems. Because,

- Biology provides highly automated, robust and effective organism
- Search strategy of bacteria is salutary (like common fish) in nature
- Bacteria can sense, decide and act so adopts social foraging (foraging in group**s).**

2. DESIGN ASPECTS

The general requirements of the lenses are as follows:

The lenses should be of rectangular shape with its length dependent on the focal length of the lens itself, the distance at which the module is to be placed and the length of the module on which the rays have to be focused.

The breadth of the lens should be equal to the breadth of the photovoltaic module used.

According to lens maker's formula for Plano convex lens [16], [17].

$$1/f = (\mu - 1)(1/R) \tag{1}$$

Variation of the focal point (f) depends on refractive index of the lenses (μ) and radius of curvature of the lenses (R)

These variations shown in the table-1 are obtained using equation (1).

Table 1
Refractive index vs radius of Curvature

μ	1.5	1.33	1.25	…	1.10	…	1	<1
f	2R	3R	4R	…	10R	…	∞	-kR

When the refractive index of a glass is 1, the focal distance will be infinity and when it is less than 1, and then the focal length will be negative. For a lens of same refractive index the focal distance can be varied by varying the radius of curvature of the lens and vice versa.

3. ANGLE CALCULATION

In this design, the angle at which the side lenses are to be placed with respect to the horizontal lens holds a key in order to utilize the module with maximum efficiency[19]. The placement of the module mainly depends on R, μ and f.

i.e. θ varies depending on the variations in R and μ, but it mainly depends on f. The variation of θ with respect to f is given by

$$\theta = (70° + Y\,10°) + 47.5° \tag{2}$$

Where $Y = 0, 1, 2,$ —— and $f = 2R + YR$.

The value of Y is selected depending on the variation of 'f' with respect to μ as given in table-1.The focal point also varies depending on the variations in radius of curvature of the lens at

Constant refractive index and hence variation of angle takes place.

Here R is taken as $R = 2.5\,X$ Where $X = 1, 4/5, 3/5, 2/5$.

For a length of $5X$ of the lens, so that the related values can be easily calculated for various lengths of the module by making it multiples of 5.

For the values other than this R goes in to decimal values for which the calculations are difficult.

The variation of θ with respect to R can be formulated as

$$\begin{aligned} \theta &= 90° + (47.5°\,X) \text{ for } f = 4R \\ \theta &= 80° + (47.5°\,X) \text{ for } f = 3R \end{aligned} \tag{3}$$

Hence the overall variation of θ depending on the variations of f and R can combinely be formulated as

$$\begin{aligned} f &= 2R + YR \\ \theta &= (70° + Y\,10°) + (47.5°\,X) \end{aligned} \tag{4}$$

For $\mu > 1.5$, f becomes less than $2R$. For these values Plano convex lenses will not converge the radiation on to the module surface fully because of the narrowing of the path of the converged rays.

4. MODULE LENGTH

The module length is inversely proportional to the focal distance of the lenses that are being selected [19]. Hence the module can be selected based on the values of radius of curvature and refractive index of the lenses.

5. CAD SIMULATION RESULT

The formulae derived in this paper are verified by applying the various possible data through the Computer Aided Design (CAD) [18] and satisfactory results are obtained. The example is shown in figures 1.The validity of the first two formulae is verified by varying μ or R while keeping the other constant.

When the refractive index is kept constant and CAD simulations are carried out for $\mu = 1.25$, $f = 4\,R \leftrightarrow Y = 2$ and at $R = 2.5 \leftrightarrow X = 1$ Then $\theta = 117.5° + 10°\,Y$.

Thus when $\theta = 137.5°$ and $f = 10$ the result of CAD simulation is shown in Figure 1.

6. KALMAN FILTER

Kalman filter is a linear estimator and hence an assumption is made regarding the linearity of a solar cell. Fig.-2 shows the schematic diagram connecting a Kalman filter with the solar cell (plant model) and the sensor (measured

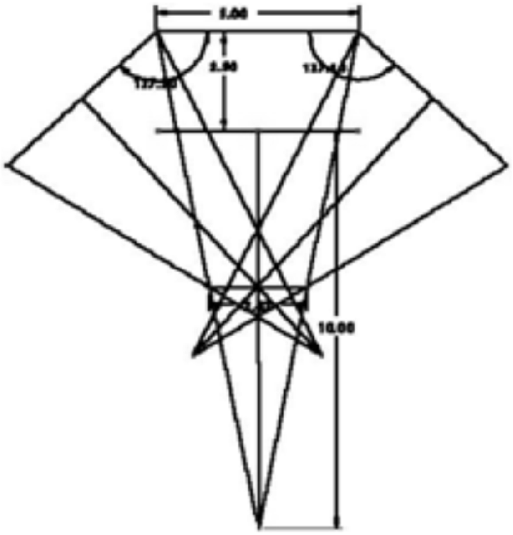
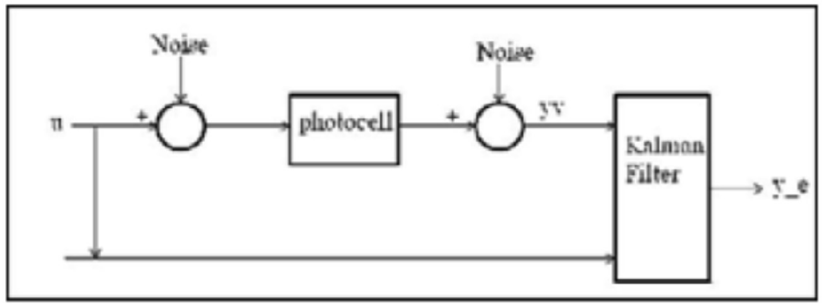


Figure 1: CAD simulations for μ = 1.25 at R = 2.5, f = 4R



u = input solar radiation flux, yv = output of the sensor, y_e = output of the Kalman filter

Figure 2: Interconnection between photocell, current sensor and Kalman filter

data)[10]. The solar cell is assumed to change its short -circuit current at the rate 10mA/second which is the input to the measuring device.

The measured data and the input data both are fed to the Kalman filter as its input. Kalman filter will have two kinds of noise embedded in its input data– the process noise (w) and the measurement noise (v)[11][12]. Both these noises are assumed to be Gaussian with zero mean as per basic assumptions of a Kalman filter. The process noise covariance (uncertainty) denoted by $Q = E(ww^T)$ and measurement noise covariance $R = E(vv^T)$, are improvised at every iteration consisting of two steps of 'predict' and 'update'. A plant model has been chosen to be a simple linear equation where short-circuit current of a photovoltaic cell is linearly rising with a constant slope due to linearly varying solar radiation flux[13]. The sensor measurement of the aforementioned current is noisy with random Gaussian noise whose covariance is known beforehand.

Initially current starts from zero due to zero radiation flux and subsequently changes at the rate of 10mA per second as the radiation flux changes.

The system dynamics φ is represented by

$$\begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix}, where\ dt = 0.1\ second$$

There are a total of N = 100, number of samples that we are dealing with. The confidence matrix P shows whether we should give more weight to the new measurement or to thesystem model. σ_{model} is varied from 0.1 to 1, to indicate the confidence on the model chosen. Similarly, σ_{meas} can be variedfrom 0.1 to 1 and it is found during simulation that σ_{model} is affecting the filtered output more than σ_{meas}. The confidence matrix P is given by,

$$\begin{bmatrix} \sigma^2_{\text{model}} & 0 \\ 0 & \sigma^2_{\text{model}} \end{bmatrix}.$$

The covariance matrix of the model is initialized with $Q = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$ that indicates a high process noise and the simulation stopsonly when Q reaches $\begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$. The null matrix signifies that our process noise covariance is zero and that we have absolute confidence on our system model. The measurement matrix M is denoted by $M = [1\ 0]$, where the first term is indicating the measurement of the current and the second term is the time derivative of current, which is zero for our case[14][15][16]. The measurement noisecovariance R derived from σ_{meas} $\left(R = \sigma_{meas}^2\right)$ and keeps varying from sample to sample. R varies in the scale of 0.1 to 1indicating the confidence in our sensor output.

7. MATHEMATICAL INTERPRETATION OF ALGORITHM

The measurement vector Z is represented by,

$$Z = X_{true}(k+1) + \sigma_{meas} \text{*random noise} \tag{5}$$

Where, X_{true} is the assumed value

$$P1 = \varphi * P * \varphi' \tag{6}$$

$$S = M * P_1 * M' + R \tag{7}$$

Kalman gain is found by the following equation

$$K = P_1 * M' * inv(S) \tag{8}$$

$$P = P_1 - K * M * P_1 \tag{9}$$

If Kalman gain shows a high value, more weight is given to the measurement, and if Kalman gain is low, then an emphasis is given on model prediction[17].

X_k is the state estimation of the latest state and X_{k_prev} isthe state estimation of the previous state.

$$X_k = \varphi * X_{k\_prev} + K * (Z - M * \varphi * X_{k\_prev}) \tag{10}$$

A single step of iteration is executed when we run the simulation based on equation 4 to equation 8 which calculates and buffers only the $(k-1)^{th}$ value of Q, R, K and P. Subsequently as more and more measurement data (along with random measurement error) is received, the error between the estimated value and sensor data (measurement) reduces on employing Kalman filter algorithm as stated above[18].

8. MODELLING OF BFO

Since selection behavior of bacteria tends to eliminate animals with poor foraging strategies and favor the propagation of genes of those animals that have successful foraging strategies, they can be applied to have optimal solution through methods for locating, handling and ingesting food[1][2]. After many generations, a foraging animal takes actions to maximize the energy obtained per unit time spent foraging[3][4]. That is, poor foraging strategies are either eliminated or shaped into good ones. Optimization models are also valid for social foraging where groups of animals communicate to cooperatively forage, in the face of constraints presented by its own physiology such as, sensing and cognitive capabilities and environment [5][6][7]. This activity of foraging inspired the researchers to utilize it as a novel optimization tool. The E.Coli bacteria present in our intestines also practice a foraging strategy. The control system of these bacteria governing their foraging process can be sub divided into four sections, which are chemo taxis, swarming, reproduction and elimination and dispersal [8]. Figure 3 shows the characteristics of bacterium.

Solar radiation power data was recorded in terms of current and voltages. In order to calculate the maximum power from the collected data, BFO algorithm was used. Table 4, show sestimation of minimum number of bacteria for finding maximum power and hence its location. Readings were taken during afternoon and evening time. It is observed that different numbers of bacteria required to get power estimated at different time of intervals.

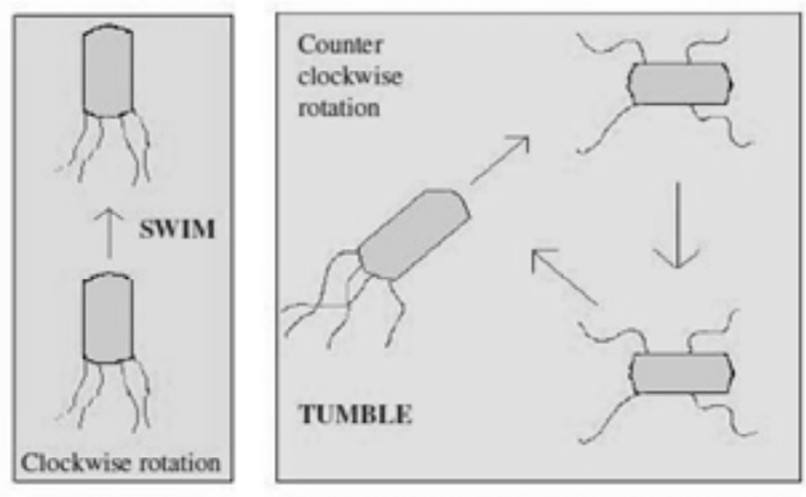


Figure 3: Swim and Tumble of a bacterium

Table 2
Comparison of True Current, Measured Current by a Sensor and Kalman Estimated Current with BFO

Time (s)	*True current (mA)*	*Measurement (mA)*	*Kalman estimated current (mA)*
0.5	4.225	5.261	5
0.6	6	5.059	4.846
0.7	7	6.838	5.7
0.8	8	7.854	6.611
0.9	9	12.58	7.326
1	10	11.68	8.852
2	20	21.6	19.25
3	30	28.75	29.45
4	40	40.93	39.35
5	50	51.11	49.59
6	60	61.12	59.6
7	70	72.35	69.72
8	80	79.8	79.62
9	90	88.83	89.78
10	100	98.21	99.7

Table 3
Comparing Running Average Current and Kalman Filter With BFO Output

Time (second)	*True deviation of current (mA)*	*Estimated current by running average (mA)*	*Estimated current by Kalman filter (mA)*
1	10	9.407	6.654
2	10	11.4	8.99
3	10	7.448	9.495
4	10	12.47	9.544
5	10	13.95	9.746
6	10	12.25	9.807
7	10	5.676	9.838
8	10	11.14	9.875
9	10	9.277	9.919
10	10	7.744	9.918

Kalman filter is found to produce a close prediction of short-circuit current than moving average filter as shown in figure 4.

Table 4
Results of solar power optimization using BFO algorithm

No of Bacteria Afternoon	*Estimated Power*	*Inclined Axis* L_1	*Horizontal axis angles* L_2
6	76.0430	75	300
10	72.6800	76	310
14	72.3600	46	280
18	73.7080	76	220
22	74.7080	76	250
26	77.3840	76	250
30	92.9440	76	340
	Evening		
6	72.3060	15	150
10	76.6000	30	210
14	76.6000	30	210
18	77.5320	30	270
22	78.5320	30	270

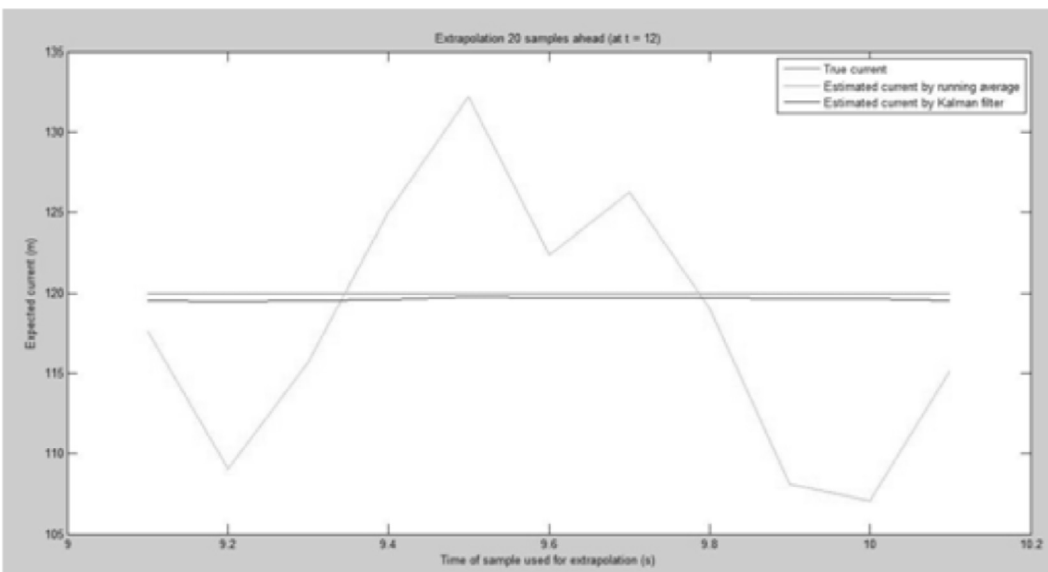


Figure 4: Short circuit current through Kalman filter with BFO

For example, as per Table 4, the six number of bacteria get 76.043(mW) estimated power at 75 vertical axis and 300 horizontal axis angles in afternoon time,but get 72.3060(mW) estimated power at 15 vertical axis and 150 horizontal axis angles in evening time. It is also observed that however number of bacteria increases, the estimated power also increases respectively with different vertical and horizntalangles to track maximum power point. Thus at least more than 30 bacteria must be used to find maximum point. Fig. 3 shows 3D-graphical presentation of the results of solar power optimization using BFO algorithm at different time of inter valw.r.t.vertical angle (L_1) and horizontal angle (L_2). During afternoon and evening time with bacteria size 30 and 22 respectively.

9. RESULTS AND DISCUSSION

Kalman filter can estimate as well as predict a linear system very closely, but the plant model has to be accurate. To estimate and predict with higher precision more emphasis should be given on plant model than the sensor model. Kalman filter can be termed as second generation estimator as compared to its first generation counterpart like moving average filter. It is not necessary to know the initial state of the system and hence Kalman filter can be used in the problem of filtering, smoothing and prediction.Solar radiation power data was recorded in terms of current and voltages. In order to calculate the maximum power from the collected data, BFO algorithm was used.

The concentrators having thermal impact on the solar panel in turn helps to improve the power output. The simulation result shows the Kalman filter with BFO will give constant power output during day hours for normal sunny day. From table-4 it is understood that the BFO algorithm is having its own impact with respect to time on output power.

10. CONCLUSION

Its adjustable design, capable of a variety of concentration ratios of solar irradiation and its use of concentrating lenses typically used by conventional solar concentrating systems (for conversion of infrared (IR) solar energy to heat energy), allows our SCS to directly and simply substitute for conventional (solar trough and solar tower) concentrating systems at considerably lower manufacturing and maintenance cost, and to use the trough system's already well-established approaches for solar-thermal-electrical energy conversion applications of concentrating solar systems. The most important advantage of our solar concentrating system (SCS) is that its cost is substantially less (roughly 30%) than the cost of most existing solar concentrating system, with similar energy efficiency. It requires no large-scale structural support structures for the primary concentrators, which vastly decreases construction costs. In contrast, most prior SCS's primary concentrator's require costly support structures and tracking systems. It was carefully tailored to very substantially decrease manufacturing costs without decreasing energy efficiency.

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