

GENETIC ALGORITHM FOR THE MAXIMUM OPERATING POINT IN PHOTOVOLTAIC SYSTEM

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Abstract: This paper presents an intelligent control method for the maximum power point tracking (MPPT) of a photovoltaic system under variable temperature and irradiance conditions. This paper presents a Genetic Algorithm (GA) to meet the maximum power operating point whatever the climatic conditions are from simulation results, it has been found that GA method is highly competitive for its better convergence performance.

Key words: photovoltaic system, MPPT, optimization technique, Genetic Algorithm (GA).

Nomenclature

q	Electronic charge
k	Voltzmann's constant
η	Diode ideality factor
G	Insulation level
T	Cell temperature
R_s	Cell series resistance
R_{sh}	Cell Shunt resistance
I_o	Reverse saturation current
I_D	Diode current
I_L	Photo current
I_{sc}	Short-circuit.
V_{oc}	The open circuit
V_k	Current velocity
N	Population size
P_C	Crossover probability
P_M	Mutation probability
K_{max}	Maximum number of iterations
K	Current number of iterations,

1. Introduction

Photovoltaic energy is a technique, which converts directly the sunlight into electricity. It is modular, quit, non-polluting and requires very little maintenance, for this reason a powerful attraction to photovoltaic systems is noticed. By having a quick glance on both the current-voltage and the power-voltage characteristics of PV arrays, we see clearly the dependence of the generating

power of a PV system on both insulation and temperature. [1].

In this study, we present an application of a Genetic Algorithm Optimization (GA) on a photovoltaic system, which helps to catch the Maximum Power Operating Point (MPOP). This latter change instantaneously with changing radiation and temperature, what implies a continuous adjustment of the output voltage to achieve the transfer of the maximum power to the load. The justification of this application lies in the fact the I-V and P-V characteristics are non linear because of the nonlinearity of the photovoltaic systems from one hand and because of the instantaneous change of both insulation and temperature from the other hand, what makes the two previous plot in fact fluctuating instead of the simulated smooth ones (Fig. 1 and 2). [2]

Therefore, the adoption of this novel adaptive GA technique offers the possibility of dealing accurately with these optimization problems and to overcome the incapacities of the traditional numerical techniques.

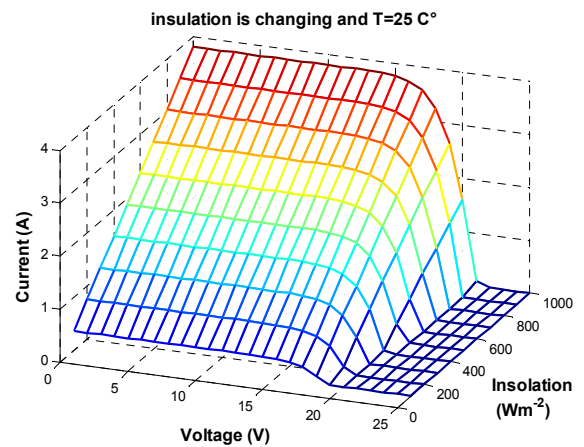


Fig. 1. I-V characteristics when insulation is changing.

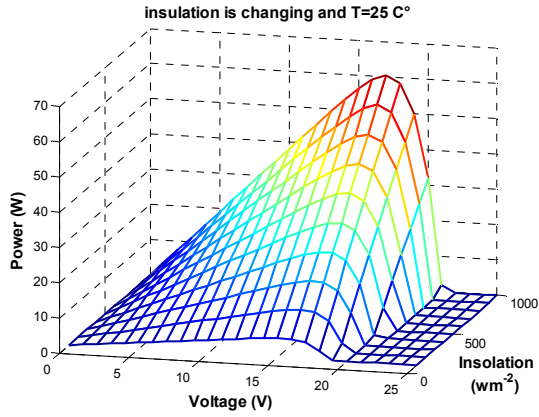


Fig. 2. P-V characteristics when insulation is changing.

The proposed approach is employed in fitting both the I-V and P-V characteristics of a solar module referenced as Solarex MSX 60 with the characteristics shown in the index.

2. Modeling of the photovoltaic generator

Thus the simplest equivalent circuit of a solar cell is a current source in parallel with a diode. The output of the current source is directly proportional to the light falling on the cell (photocurrent I_{ph}). During darkness, the solar cell is not an active device; it works as a diode, i.e. a p-n junction. It produces neither a current nor a voltage. However, if it is connected to an external supply (large voltage) it generates a current I_D , called diode (D) current or dark current. The diode determines the I-V characteristics of the cell.

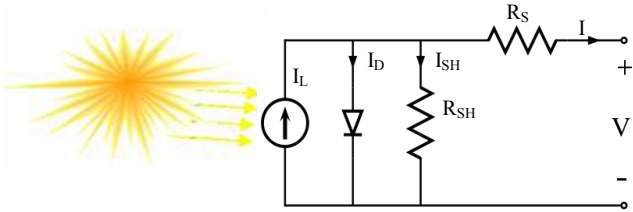


Fig. 3. Circuit diagram of the PV model.

Increasing sophistication, accuracy and complexity can be introduced to the model by adding in turn [3]:

- Temperature dependence of the diode saturation current I_0 .
- Temperature dependence of the photo current I_L .
- Series resistance R_S , which gives a more accurate shape between the maximum power point and the open circuit voltage. This represents the internal losses due to the current flow.
- Shunt resistance R_{sh} , in parallel with the diode, this corresponds to the leakage current to the ground and it is commonly neglected
- Either allowing the diode quality factor n to become a variable parameter (instead of being fixed at either 1 or

- 2) or introducing two parallel diodes with independently set saturation currents.

In an ideal cell $R_S = R_{sh} = 0$, which is a relatively common assumption [4]. For this paper, a model of moderate complexity was used. The net current of the cell is the difference of the photocurrent, I_L and the normal diode current I_0 :

$$I = I_L - I_0 \left(e^{\frac{q(V + IR_S)}{nkT}} - 1 \right) \quad (1)$$

The model included temperature dependence of the photocurrent I_L and the saturation current of the diode I_0 .

$$I_L = I_L(T_1) + K_o(T - T_1) \quad (2)$$

$$I_L(T_1) = I_{sc}(T_{1,nom}) \frac{G}{G_{(nom)}} \quad (3)$$

$$K_o = \frac{I_{sc}(T_2) - I_{sc}(T_1)}{(T_2 - T_1)} \quad (4)$$

$$I_0 = I_0(T_1) \times \left(\frac{T}{T_1} \right)^{\frac{3}{n}} e^{\frac{qV_q(T_1)}{nk} \left(\frac{1}{T} - \frac{1}{T_1} \right)} \quad (5)$$

$$I_0(T_1) = \frac{I_{sc}(T_1)}{e^{\frac{qV_{oc}(T_1)}{nkT_1}} - 1} \quad (6)$$

A series resistance R_S was included; which represents the resistance inside each cell in the connection between cells.

$$R_S = -\frac{dV}{dI_V} - \frac{1}{X_V} \quad (7)$$

$$X_V = I_0(T_1) \times \frac{q}{nkT_1} e^{\frac{qV_{oc}(T_1)}{nkT_1}} - \frac{1}{X_V} \quad (8)$$

The shunt resistance R_{sh} is neglected. A single shunt diode was used with the diode quality factor set to achieve the best curve match. This model is a simplified version of the two diode model presented by Gow and Manning [5]. The circuit diagram for the solar cell is shown in Figure 3.

The I-V characteristics of the module can be expressed roughly by the Eq. 1-8. the model requires three point to be measured to define this curve: [6].

- The voltage of the open circuit V_{oc} .
- The current of short-circuit I_{sc} .
- The point of optimum power (I_{opt} , V_{opt}).

3. Genetic Algorithm optimization approach

Genetic Algorithms (GA) are search algorithm based on mechanics of natural selection and natural genetic [7]. The laws of coincidence take advantage of pre information in order to derive improvement from it.

GA are algorithm for optimization based on the principal of biological search algorithm in the sense that they simultaneously consider many points in the search space.

They work not with the parameters themselves but with string of numbers representing the parameter set. And they are probabilistic rules to guide their search. By considering many points in the search space simultaneously reduce the change of converging to local minimal.

The process of GA follows this pattern [8].

- 1) Create an initial population (usually randomly generated string).
- 2) Evaluate all of the individuals (apply some function or formula to the individuals).
- 3) Select a new population from the old population based on the fitness of the individuals as given by the evaluation function.
- 4) Apply some genetic operators (mutation & crossover) to members of the population to create new solutions.
- 5) Evaluate these newly created individuals.
- 6) Repeat steps 3-6 (one generation) until the termination criteria has been satisfied (usually perform for a certain fixed number of generations).

The concept of implementation sequence is the survival of the fittest. The reproductive success of a solution is directly tied to the fitness value, which is assigned during evaluation. The least fit solution may not reproduce at all. The major advantage of GA lies in their computational simplicity, and their powerful search ability to obtain the global optimum. The further attraction of GA is that they are extremely robust with respect to complexity of the problem.

4. Application of GA to MPOP

The goal is to solve some optimization problem where we search for an optimal solution in terms of the variables of the problem (current and voltage) by imposing the constraints on the current and the voltage which should be both bigger than zero.

To minimize F is equivalent to getting a maximum fitness value in the searching process. The objective of GA has to be changed to the maximization of fitness to be used as follows:

$$fitness = \begin{cases} P(V, I) / P_{max}; & \text{if } P_{max} < P \\ 0; & \text{otherwise} \end{cases} \quad (9)$$

The power given by (9) is a non-linear function of current and voltages which are a function of control variables. The maximization problem is subjected to the following equality and inequality constraints:

$$V < V_{max} \text{ and } P < P_{max}$$

The above steps and how GA evolves are depicted by the flow chart of Fig. 4. It should be noted that all the parameters involved in the genetic algorithm can be pre-defined subject to the nature of the problem being solved, which is the controlled equipment, is encoded to binary digits, and then they are located on a string. The number of string length will be chosen.

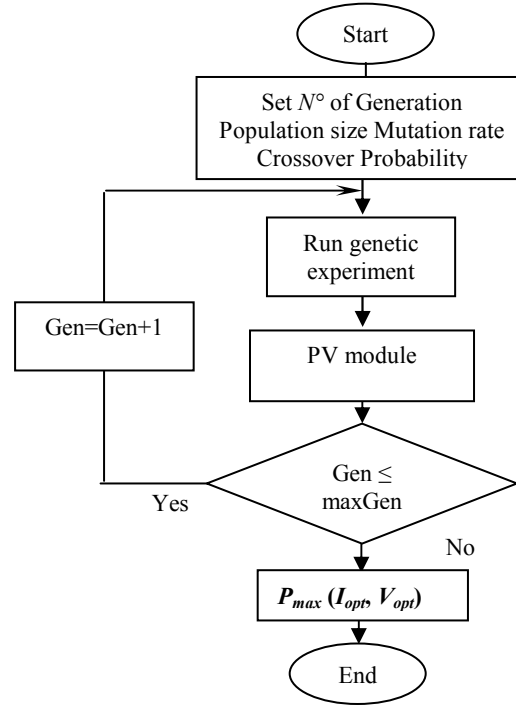


Fig. 4. Flow chart of genetic algorithm.

5. Simulation Results and Discussion

The program has been developed and executed under MATLAB system. The program was written and executed on Pentium 4 having 2.4 GHZ 1GB DDR RAM.

In all the experiment the following GA was adopted and held constant.

$N = 50$, $P_C = 0.9$, $P_M = 0.03$, $K_{max} = 50$.

The resulted values of this optimization problem are shown in simulation 1-2. These simulation results of many sample runs of the GA technique. We see clearly the variation of the MPOP with respect to either insulation or temperature and both of them with great accuracy (Fig. 9-12).

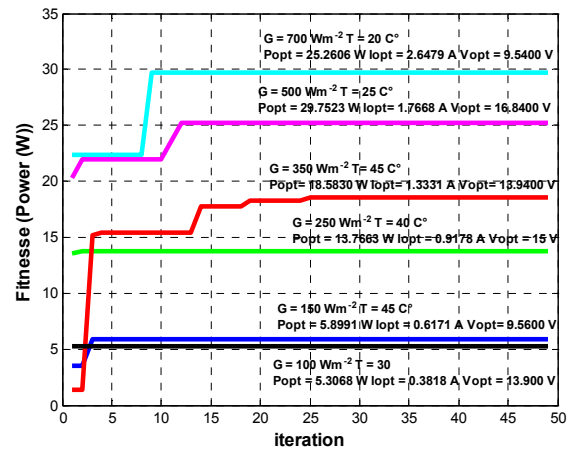


Fig. 5. Convergence of GA under different conditions

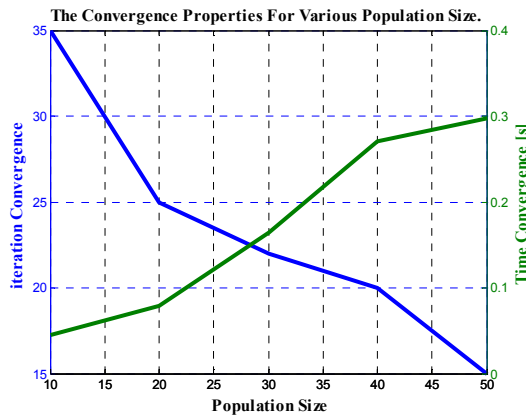


Fig. 6. the convergence properties for various population size

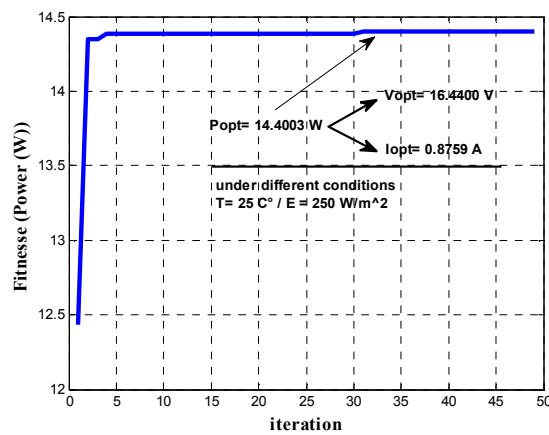


Fig. 7. Convergence of GA for $T = 25\text{ C}^\circ$ and $E = 250\text{ Wm}^{-2}$

The convergence of optimal solution using GA is shown in Fig. 5 and 7, where only about 25 iterations were needed to find the optimal solution. However, GA may be allowed to continue the search in the neighborhood of the optimal point to increase the confidence in the result. GA stops after 50 iterations and returns the optimal value.

In order to simulation the system, it is necessary to use the irradiance data for a specific location over 24 a hour period of time, any location will be sufficient to test the model. I chose to use data from Golden, Colorado on March 14, 2010 and July 14, 2009 because the data is easily available, and I can be reasonably confident about the accuracy [9]. The data for July 14, 2009 appears to be a pretty good example of a typical sunny day, while March 14, 2010 is good worst case scenario (refer to fig. 8 and 9). Both of these days can be useful for simulation purposes.

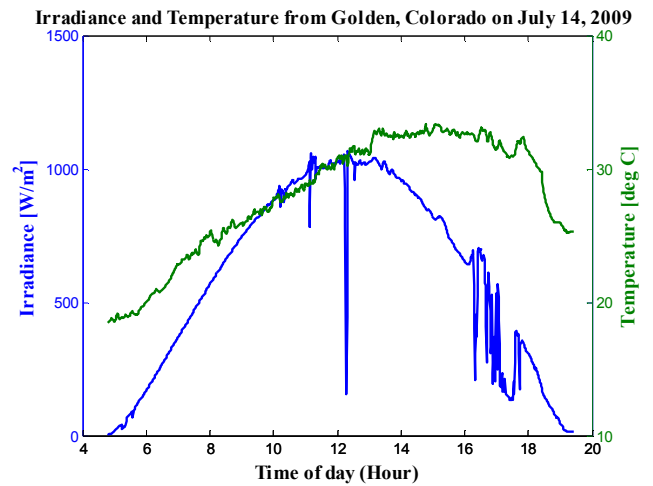


Fig. 8. Irradiance and Temperature data for sunny day simulation purposes.

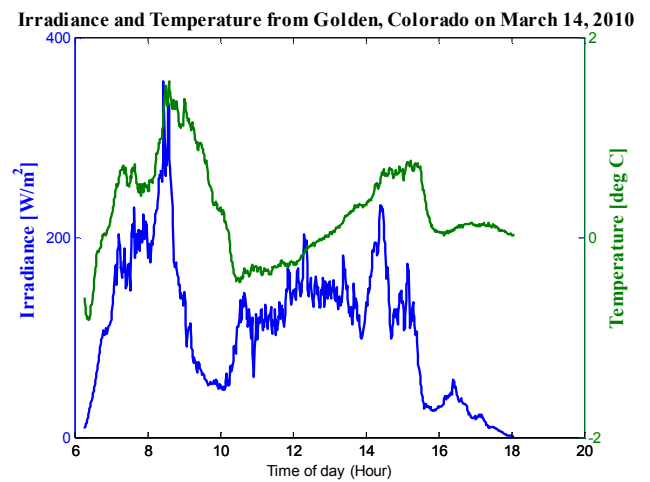


Fig. 9. Irradiance and Temperature data for cloudy day simulation purposes.

Simulation 1 : Sunny day conditions.

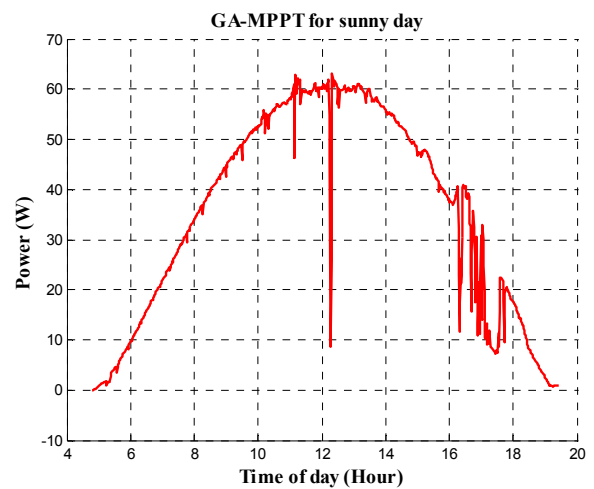


Fig. 10. Power optimal for sunny day simulation purposes.

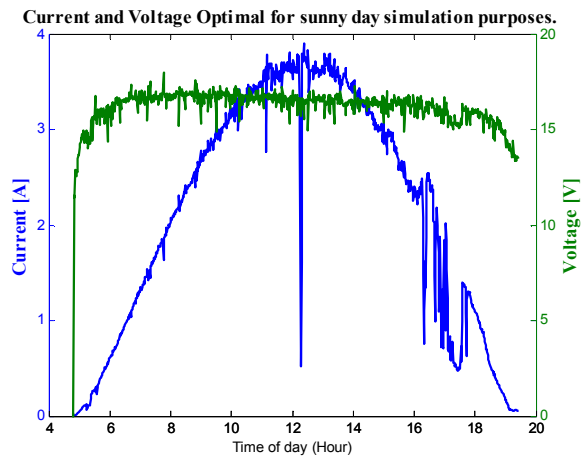


Fig. 11. Current and Voltage optimal for sunny day simulation purposes.

Simulation 2 : Cloudy day conditions.

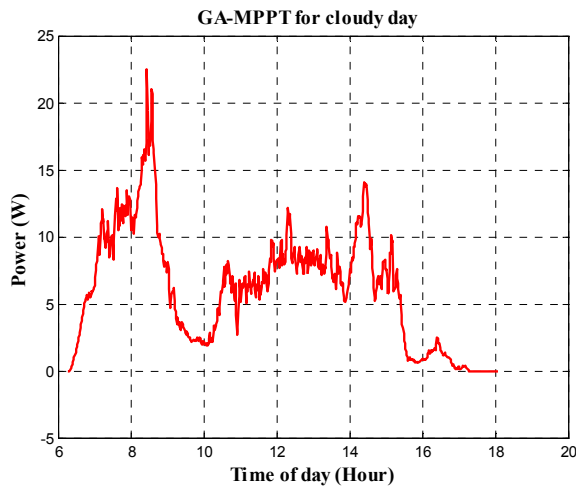


Fig. 12. Power optimal for cloudy day simulation purposes.

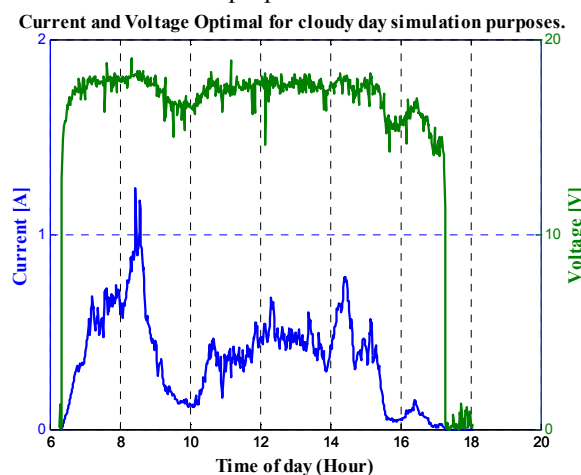


Fig. 13. Current and Voltage optimal for cloudy day simulation purposes.

Obviously, the system works much better under sunny conditions. The data used for the cloudy day dropped the

power maximal of PV array by about 80 % , indicating that the maximum of two consecutive cloudy days can be handled by the system.

However given the significant decrease in energy produced by the PV array, there may have been another factor (snow for example) that would not have been such an issue at a lower latitude. Therefore, I would recommend that simulations be run for several more cloudy day scenarios. Also, a simulation in which cloudy day is followed by a sunny day may give us an idea of how quickly the system would be able to rebound back to normal condition.

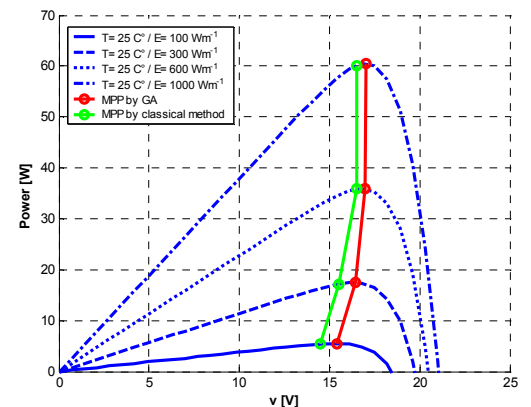
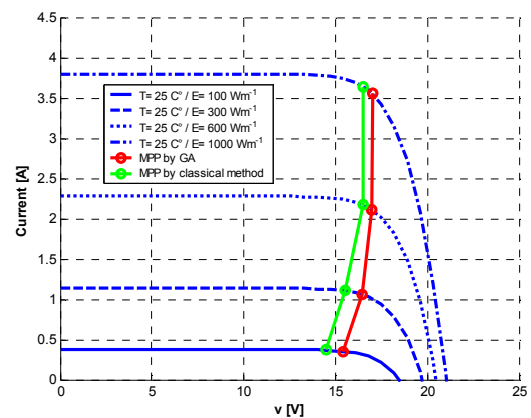
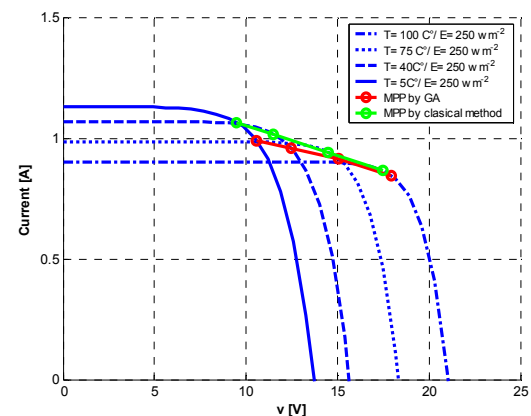


Fig. 14. compares the PV array characteristics with insulation.



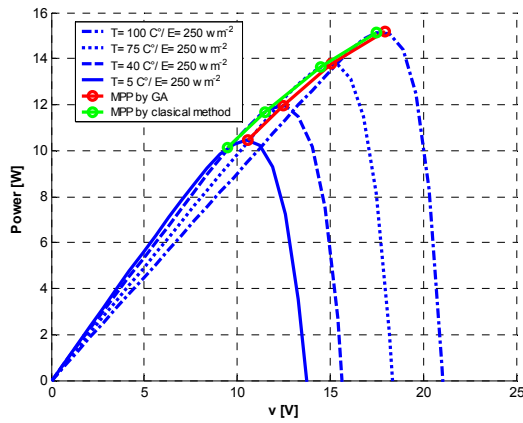


Fig. 15. compares the PV array characteristics with temperature.

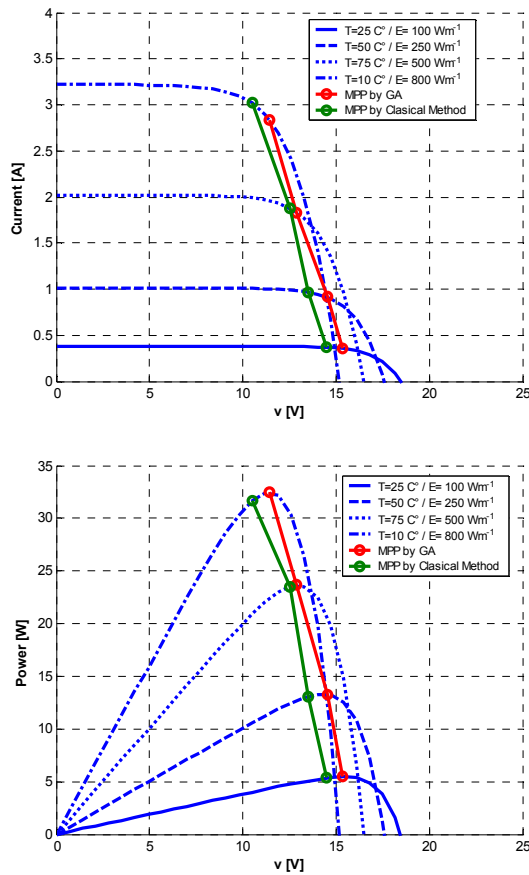


Fig. 16. compares the PV array characteristics with insulation and temperature.

The Fig. 14 -16 compares the PV array P-V characteristics obtained from using the proposed MPPT with GA and the classical MPPT P&O algorithm. From this figure, it can be seen that by using the proposed MPPT algorithm, the operating point of PV array is much closer to the MPP compared to the using the classical P&O algorithm.

6. Conclusion

This paper introduces a new solution approach based on Genetic Algorithm, which calculates instantaneously the MPOP of a PV module in order to maximize the profits in terms of the power issued from the PV module. Because of the P-V characteristics this heuristic method is used to seek the real maximize power and to avoid the wrong values of local maxima. The obtained results of this investigation and depicted in Fig. 10-13.

The usefulness of a model for a GA technique should prove to be significant. It is not difficult to simulate a variety of conditions or make change to parameters in the system. It is easy to probe values from any point on the model in order to better understand the relationships between different components. Despite some minor difficulties, however the model performs beautifully, and is not overly difficult to use.

The optimal Power solutions determined by GA is well capable of determining the global or near global maximum power operating point.

Major drawback of GA, is that it lacks somewhat a solid mathematical foundation for analysis to be overcome in the future.

Appendix

Appendix 1 : Solarex MSX 60 Specifications (1kW/m², 25°C)

Characteristics	SPEC.
Typical peak power (P_m)	60W
Voltage at peak power (V_m)	17.1V
Current at peak power (I_m)	3.5A
Short-circuit current (I_{sc})	3.8A
Open-circuit voltage (V_{oc})	21.1V
Temperature coefficient of open-circuit voltage (α)	-73 mV/°C
Temperature coefficient of short-circuit current (β)	3 mA/°C
Approximate effect of temperature on power	-0.38W/°C
Nominal operating cell temperature (NOCT ²)	49°C

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