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International
Journal
Of Modern Engineering Research (IJMER)

Big Bang–Big Crunch Optimization Algorithm for the Maximum Power Point Tracking 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. The Big Bang–Big Crunch (BB–BC) optimization algorithm is a new optimization method that relies on the Big Bang and Big Crunch theory, one of the theories of the evolution of the universe. In this paper, a Big Bang–Big Crunch algorithm is presented to meet the maximum power operating point whatever the climatic conditions are from simulation results, it has been found that BB–BC method is highly competitive for its better convergence performance.*

Keywords: *Photovoltaic System, MPPT, Optimization Technique, Big Bang–Big Crunch (BB–BC)*

I. NOMENCLATURE

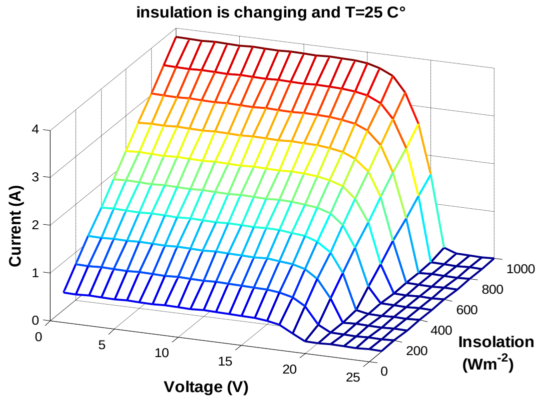
BB-BC	big bang–big crunch
G	insulation level
I_D	diode current
I_L	photo current
I_o	reverse saturation current
I_{sc}	short-circuit.
k	boltzmann's constant
l	upper limit
MPPT	maximum power point tracking
PV	solar photovoltaic
q	electronic charge
R_s	cell series resistance
R_{sh}	cell Shunt resistance
T	cell temperature
V_{oc}	the open circuit
x^c	center of mass

II. INTRODUCTION

Photovoltaic energy is a technique, which coverts 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].

A new optimization method relied on one of the theories of the evolution of the universe namely, the Big Bang and Big Crunch theory is introduced by Erol and Eksin [11] which has a low computational time and high convergence speed. According to this theory, in the Big Bang phase energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order. The Big Bang–Big Crunch (BB–BC) Optimization method similarly generates random points in the Big Bang phase and shrinks these points to a single representative point via a center of mass in the Big Crunch phase. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution. The BB–BC method has been shown to outperform the enhanced classical Genetic Algorithm for many benchmark test functions [2].

In this study, we present an application of a Big Bang–Big Crunch (BB–BC) 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) [3].



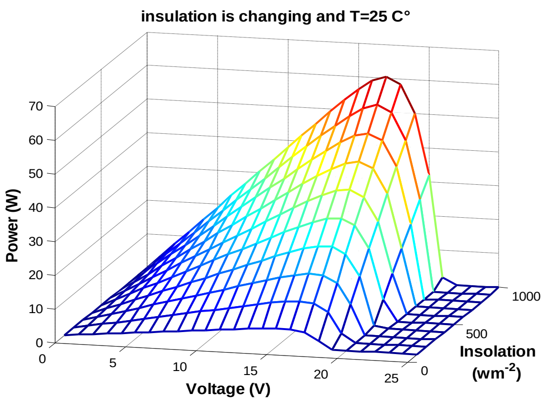


Fig. 1 I-V characteristics when insulation is changing. Fig. 2 P-V characteristics when insulation is changing.

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.

III. 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.

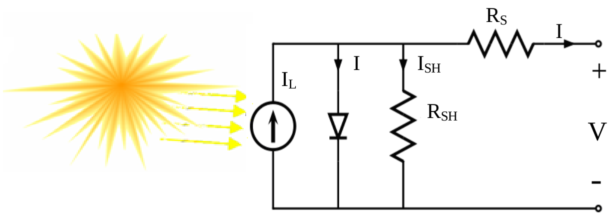


Fig. 3 Circuit diagram of the PV model.

Increasing sophistication, accuracy and complexity can be introduced to the model by adding in turn [4]:

- 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 [5]. 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:

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

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

$$I_L = I_L(T_1) + K_o(T - T_1), \tag{2}$$

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

$$K_o = \frac{I_{SC}(T_2) - I_{SC}(T_1)}{(T_2 - T_1)}, \tag{4}$$

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

$$I_o(T_1) = \frac{I_{SC}(T_1)}{(e^{\frac{qV_{OC}(T_1)}{nkT_1}} - 1)}, \tag{6}$$

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

$$R_S = -\frac{dV}{dI_V} - \frac{1}{X_V}, \tag{7}$$

$$X_V = I_o(T_1) \times \frac{q}{nkT_1} e^{\frac{qV_{OC}(T_1)}{nkT_1}} - \frac{1}{X_V}, \tag{8}$$

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 [6]. 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 (1) to (8). the model requires three point to be measured to define this curve [7]:

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

IV. BIG BANG–BIG CRUNCH (BB–BC) OPTIMIZATION ALGORITHM

The BB–BC method developed by Erol and Eksin [2] consists of two phases: a Big Bang phase, and a Big Crunch phase. In the Big Bang phase, candidate solutions are randomly distributed over the search space. Similar to other evolutionary algorithms, initial solutions are spread all over the search space in a uniform manner in the first Big Bang. Erol and Eksin [2] associated the random nature of the Big Bang to energy dissipation or the transformation from an ordered state (a convergent solution) to a disorder or chaos state (new set of solution candidates).

Randomness can be seen as equivalent to the energy dissipation in nature while convergence to a local or global optimum point can be viewed as gravitational attraction. Since energy dissipation creates disorder from ordered particles, we will use randomness as a transformation from a converged solution (order) to the birth of totally new solution candidates (disorder or chaos) [2].

The proposed method is similar to the GA in respect to creating an initial population randomly. The creation of the initial population randomly is called the Big Bang phase. In this phase, the candidate solutions are spread all over the search space in an uniform manner [2].

The Big Bang phase is followed by the Big Crunch phase. The Big Crunch is a convergence operator that has many inputs but only one output, which is named as the ‘‘center of mass”, since the only output has been derived by calculating the center of mass. Here, the term mass refers to the inverse of the merit function value [8]. The point representing the center of mass that is denoted by x_c is calculated according to:

$$\vec{x}^c = \frac{\sum_{i=1}^{N} \frac{1}{f^i}\vec{x}^i}{\sum_{i=1}^{N} \frac{1}{f^i}}, \tag{8}$$

where x_i is a point within an n-dimensional search space generated, f_i is a fitness function value of this point, N is the population size in Big Bang phase. The convergence operator in the Big Crunch phase is different from 'exaggerated' selection since the output term may contain additional information (new candidate or member having different parameters than others) than the participating ones, hence differing from the population members. This one step convergence is superior compared to selecting two members and finding their center of gravity. This method takes the population members as a whole in the Big-Crunch phase that acts as a squeezing or contraction operator; and it, therefore, eliminates the necessity for two-by-two combination calculations [2].

After the second explosion, the center of mass is recalculated. These successive explosion and contraction steps are carried repeatedly until a stopping criterion has been met. The parameters to be supplied to normal random point generator are the center of mass of the previous step and the standard deviation. The deviation term can be fixed, but decreasing its value along with the elapsed iterations produces better results.

After the Big Crunch phase, the algorithm creates the new solutions to be used as the Big Bang of the next iteration step, by using the previous knowledge (center of mass). This can be accomplished by spreading new off-springs around the center of mass using a normal distribution operation in every direction, where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases [8]:

$$x^{new} = x^c + l.r/k, \tag{9}$$

where x^c stands for center of mass, l is the upper limit of the parameter, r is a normal random number and k is the iteration step. Then new point x_{new} is upper and lower bounded.

The BB–BC approach takes the following steps [2]:

Step 1 Form an initial generation of N candidates in a random manner. Respect the limits of the search space.

Step 2 Calculate the fitness function values of all the candidate solutions.

Step 3 Find the center of mass according to (9). Best fitness individual can be chosen as the center of mass.

Step 4 Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse of using (9).

Step 5 Return to Step 2 until stopping criteria has been met.

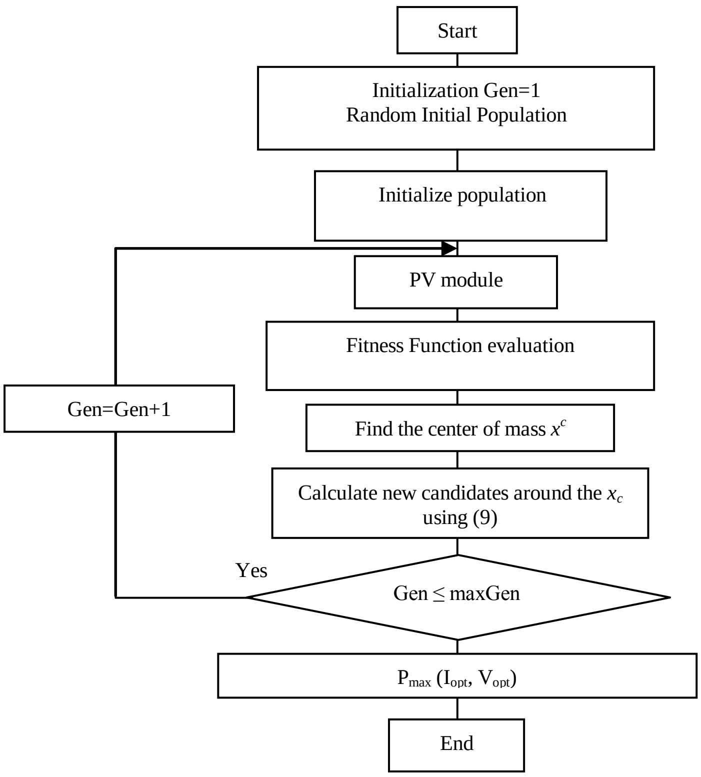


Fig. 4. Flow chart of genetic algorithm

V. APPLICATION OF BB-BC 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 fitness is equivalent to getting a maximum puissance value in the searching process. The objective of BB-BC has to be changed to the maximization of fitness to be used as follows:

$$fitness = \begin{cases} P_{\max} / P(V,I); & if \quad P < P_{\max} \\ 0; & otherwise \end{cases}, \qquad (10)$$

The above steps and how BB-BC evolves are depicted by the flow chart of Fig. 4. It should be noted that all the parameters involved in the Bang and Big Crunch algorithm can be pre-defined subject to the nature of the problem being solved, which is the controlled equipment and then they are located on a string.

VI. SIMULATION RESULTS AND DISCUSSION

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

According to simulation, the following parameters in the BB–BC algorithms methods are used :

- The number of generation is 50 iterations and Size of population 20 individuals (candidates).
- The individual having maximum fitness value is chosen for Big-Crunch phase.
- New population (Big Bang phase) is generated by using normal distribution principle with (9):

$$X(k,i)= X_{est}(i)+(X_{\max}(i)\text{-}X_{\min}(i)).rand/it, \qquad (11)$$

Where k number of candidates, i number of parameters, $X_{est}(i)$ value which falls with minimum cost, $X_{max}(i)$ and $X_{min}(i)$ are parameter upper and lower limits and it number of iterations.

The convergence of optimal solution using BB-BC is shown in Fig. 5 and 6, where only about 16 iterations were needed to find the optimal solution.

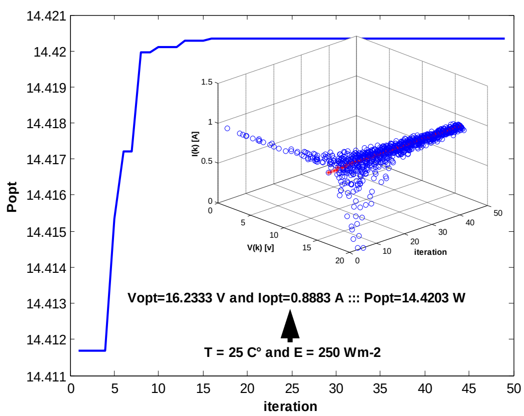


Fig. 5 Convergence of BB-BC for T = 25 C° and E = 250 Wm^{-2}

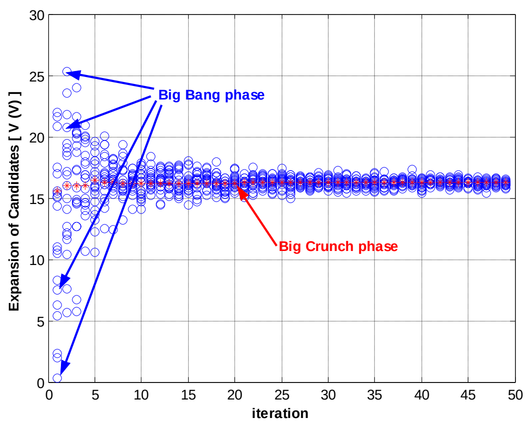
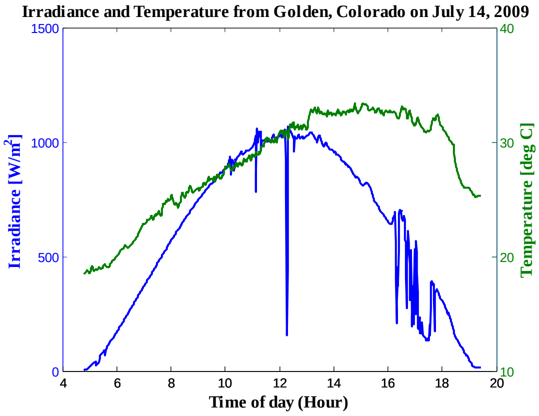


Fig. 6 Expansion of Candidates for iteration.

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.

The resulted values of this optimization problem are Show in simulation 1-2. These simulation results of many sample runs of the BB-BC 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).



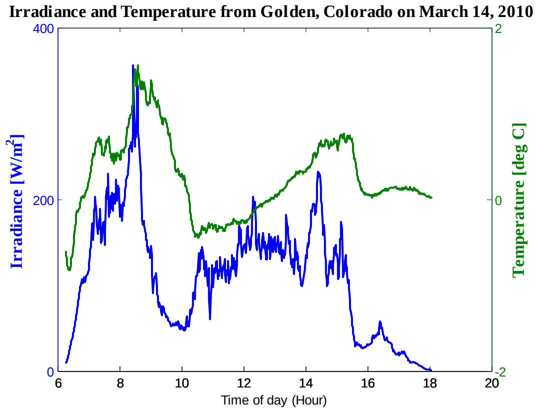
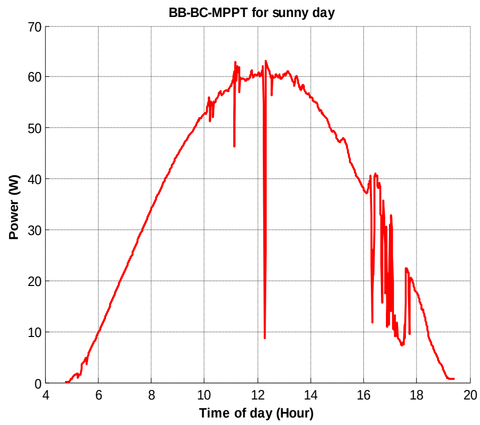


Fig. 7 Irradiance and Temperature data for sunny day. Fig. 8 Irradiance and Temperature data for cloudy day.

A. Simulation 1 : Sunny day conditions.



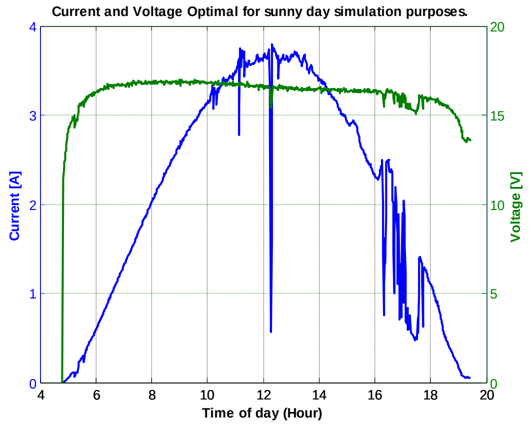
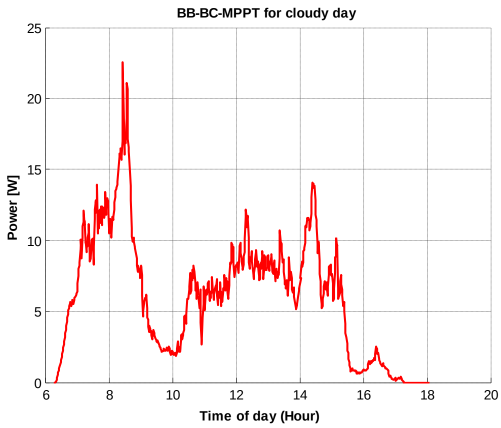


Fig. 9 Power optimal for sunny day simulation purposes. Fig. 10 Current and Voltage optimal for sunny day.

B. Simulation 2 : Cloudy day conditions.



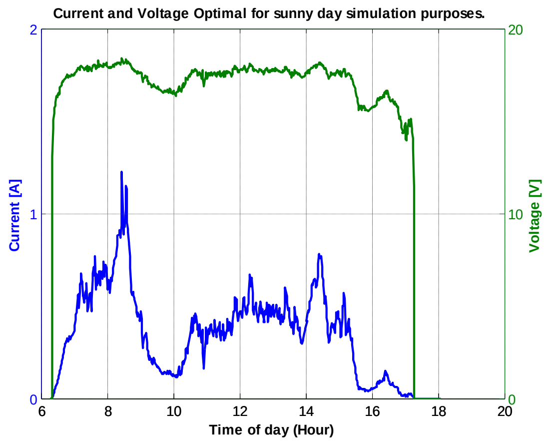


Fig. 11 Power optimal for cloudy day simulation purposes. Fig. 12 I and V optimal for cloudy day simulation purposes.

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 %.

However given the significant decrease in energy produced by the PV array, there may have been another factor (snow for example). 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 haw quickly the system would be able to rebound back to normal condition.

VII. CONCLUSION

This paper introduces a new solution approach based on Big Bang–Big Crunch, 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 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. 9-12.

The BB-BC optimization has several advantages over other evolutionary methods: Most significantly, a numerically simple algorithm and heuristic methods with relatively few control parameters; and the ability to solve problems that depend on large number of variables.

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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