OPTIMISATION USING METAHEURISTIC ALGORITHMS IN ELECTRICAL SYSTEMS

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In the partial fulfillment of the award of the degree of

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Submitted by:

Rushikesh Deshmukh

Mandar Deshpande

Mohit Karekar

Aishwarya Rajguru

UNDER THE GUIDANCE OF

Dr. V. S. Kale

Associate Professor, Department Of Electrical Engineering,

VNIT, Nagpur

VISVESVARAYA NATIONAL INSTITUTE OF TECHNOLOGY, NAGPUR

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CERTIFICATE

This is to certify that the project work entitled ***"OPTIMISATION USING METAHEURISTIC ALGORITHMS IN ELECTRICAL SYSTEMS"*** *is a bonafide work by Rushikesh Deshmukh ,Mandar Deshpande, Mohit Karekar, Aishwarya Rajguru in the department of Electrical Engineering, Visvesvaraya National Institute of Technology, Nagpur, in the partial fulfillment of requirement for the award of degree* ***in Bachelor of Technology in Electrical and Electronics Engineering.***

Dr. V. S. Kale	**Dr. M. K. Khedkar**
Mentor and Coordinator,	Head of the Department,
Associate Professor, VNIT	Professor, VNIT

VISVESVARAYA NATIONAL INSTITUTE OF TECHNOLOGY, NAGPUR.

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DECLARATION

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We hereby declare that the project work entitled ***"Optimization Using Metaheuristic Algorithms In Electrical Systems"*** *is a bonafide work performed by us, the below mentioned students. This project work is being submitted and forwarded in the partial fulfillment of requirement for the Award of requirement for the Award of degree of Bachelor of Technology in Electrical and Electronics Engineering from Visvesvaraya National Institute of Technology, Nagpur.*

To the best of our knowledge this project report has not been submitted to any other institution or university.

Rushikesh Deshmukh **Mandar Deshpande**

Mohit Karekar **Aishwarya Rajguru**

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From:

Rushikesh Deshmukh

Mandar Deshpande

Mohit Karekar

Aishwarya Rajguru

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LIST OF SYMBOLS

Crow Search Algorithm:

$x^{i,iter}$: Position of i^th crow at iteration iter

$rand_i$: random number from 0-1

$flight$: Flight Length of the crows

$Memory(x^{j,iter})$: Memory location of the j^th crow at iteration iter

AP: Awareness Probability

pd : Population Dimension

Artificial Bee Colony:

x : Solution vector

φ_i : random factor

Signal Parameter Estimation:

V : instantaneous voltage measure at sampling rate

A : amplitude of periodic signal

f : Frequency of voltage

$\emptyset$: phase shift angle

Fault Location:

FL_g : Fault location given

FL_c : Fault location calculated

r : Resistance per unit kilometer

l : Inductance per unit kilometer

z : Minimum Input Voltage

R_{cal} : Calculated resistance

L_{cal} : Calculated inductance

R_f : Fault resistance

Z_{cal} : Calculated impedance

T_l : Length of transmission line

Maximum Power Point Tracking of PV:

R_S: Series Resistance of Solar cell

R_{SH}: Shunt resistance of Solar cell

I : Solar cell output current

I_D : Diode current

I_{SH} : Current through shunt resistance

I_L : Photo generated current

I_s : Dark saturation current (diode leakage current in absence of light)

q : Electron charge

n : Diode ideality factor (manufacturing value, between 1 and 2)

K : Boltzmann's constant

I_{SC} : PV Short Circuit Current

Voc : PV Open Circuit Voltage

MPP : Maximum Power Point

I_{MPP} : Current at Maximum Power

V_{MPP} : Voltage at Maximum Power

P_{MPP} : Power at MPP

FF : Fill Factor

P_{out} : PV Output Power

P_{in} : PV Input Power

η : PV Efficiency

Cuk Converter:

R_{load} : Cuk Converter Load Resistance

R_i : Cuk Converter Apparent Input Resistance

R_{MPP} : Ideal Resistance for Maximum Power

D : Duty Cycle

V_{CC} : Voltage across Coupling Capacitor of Cuk Converter

Vo : Output Voltage of Cuk Converter

I_o : Output Current

L_1 : Input side Inductor of Cuk Converter

L_2 : Output side Inductor of Cuk Converter

ΔI_{L1} : Ripple in Current through L_1

ΔI_{L2} : Ripple in Current through L_2

T : Switching Time

f_s : Switching frequency

C_c : Coupling Capacitor

ΔV_{Cc} : Ripple in Voltage across C_c

C_o : Output Capacitor

P_i : i^{th}iteration Power

Chapter 1

Introduction

1. INTRODUCTION

1.1 About the project

Many advancements in electrical systems today are taking place through the adoption of intelligent control. Use of metaheuristic algorithms is an important and upcoming artificial intelligence technique. The scope of these algorithms is checked for certain electrical problems which involve considerable complexity through traditional methods. It is seen whether use of metaheuristic algorithms simplifies these problems and reduces computation time. This project tries to solve the problems of parameter estimation of electrical signals, fault location on transmission line and maximum power point tracking (MPPT) in photo voltaic using these algorithms.

What is a metaheuristic?

According to Sörensen and Glover (2013),

> “A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms. The term is also used to refer to a problem-specific implementation of a heuristic optimization algorithm according to the guidelines expressed in such a framework.”

A metaheuristic is a high-level procedure designed to generate a heuristic that can provide a sufficiently good solution to an optimisation problem, mainly with incomplete or imperfect information. It is a primary sub-field of Stochastic Optimisation, which is a general class of algorithms and techniques which employ some degree of randomness to find optimal solutions to hard problems.

Unlike optimisation algorithms and iterative methods, metaheuristics do not guarantee that a globally optimal solution can be found on some class of problems. In case of combinatorial optimisation, by searching over a large range of possible solutions, metaheuristics can often find good global solutions with less computational effort than other iterative methods.

1.2 History of metaheuristics

1. The *pre-theoretical* period (until c. 1940), during which heuristics and even metaheuristics are used but not formally studied.

2. The *early period* (c. 1940 – c. 1980), during which the first formal studies on heuristics appear.

3. The *method-centric* period (c. 1980 – c. 2000), during which the field of metaheuristics truly takes off and many different methods are proposed.

4. The *framework-centric* period (c. 2000 – now), during which the insight grows that metaheuristics are more usefully described as frameworks, and not as methods.

5. The *scientific period* (the future), during which the design of metaheuristics becomes a science instead of an art.

Notable contributions in the field of metaheuristics are presented in the table below.

Year	**Event**
1952:	Robbins and Monro work on stochastic optimization methods.
1954:	Barricelli carry out the first simulations of the evolution process and use them on general optimization problems.
1963:	Rastrigin proposes random search.
1965:	Matyas proposes random optimization.
1965:	Nelder and Mead propose a simplex heuristic, which was shown by Powell to converge to non-stationary points on some problems.
1966:	Fogel et al. propose evolutionary programming.
1970:	Hastings proposes the Metropolis-Hastings algorithm.
1970:	Cavicchio proposes adaptation of control parameters for an optimizer.
1970:	Kernighan and Lin propose a graph partitioning method, related to

	variable-depth search and prohibition-based (tabu) search.
1975:	Holland proposes the genetic algorithm.
1977:	Glover proposes Scatter Search.
1978:	Mercer and Sampson propose a metaplan for tuning an optimizer's parameters by using another optimizer.
1980:	Smith describes genetic programming.
1983:	Kirkpatrick et al. propose simulated annealing.
1986:	Glover proposes tabu search, first mention of the term metaheuristic.
1989:	Moscato proposes memetic algorithms.
1992:	Dorigo introduces Ant colony optimization in his PhD Thesis.
1995:	Wolpert and Macready prove the no free lunch theorems.

Table 1. Notable contributions in metaheuristics

1.3 Classification

There are different ways to classify and describe metaheuristic algorithms. Depending on the characteristics selected to differentiate among them, several classifications are possible, each of them being the result of a specific viewpoint *(Fig. 1)*. Metaheuristics can be classified as follows:

1. *Nature-inspired vs. Non-nature inspired*

   This classification is based on the origin of the algorithm. Several algorithms such as Ant Colony Algorithm, Crow Search Algorithm and the Genetic Algorithm, are nature inspired, which means they have been derived from phenomenon occurring in nature, or from the behaviour of certain insects or animals. Other ones, such as Tabu Search and Iterated Local Search are non-nature-inspired. This is not a very strict characteristic to classify algorithms, as there are many which do not fall into both categories.

2. *Population-based vs. Single point search*

Algorithms are classified on the basis of whether they employ a population for solution finding or follow a single point approach. Population-based metaheuristics perform search processes which describe the evolution of a set of points in the search space. Examples are Genetic Algorithm and Ant Colony Optimisation. While, the single-point search work with single solutions at a time, and hence are also called trajectory methods. These include Tabu Search and Simulated Annealing.

3. *Dynamic vs. static objective function*

This classification of algorithms is based on how they make use of the objective function. If they keep the objective function same throughout the problem solving process, then they are called static. Otherwise, algorithms such as guided Local Search modify it during the search. This is done to escape from local minima.

4. *One vs. Various neighbourhood structures*

Most metaheuristic algorithms work on one single neighborhood structure. Others, such as Variable Neighbourhood Search, use a set of neighbourhood structures which gives the possibility to diversify the search by swapping between different fitness landscapes.

5. *Memory usage vs. Memory-less methods*

A very important feature to classify metaheuristics is the use they make of the search history, that is, whether they use memory or not. Memory-less algorithms perform a Markov process, as the information they exclusively use to determine the next action is the current state of the search process. Memory is used to compare the results of each iteration. It is either short-term; used for comparing consecutive solutions, or long-term; for finding the overall solution. The use of memory is nowadays recognized as one of the fundamental elements of a powerful metaheuristic.

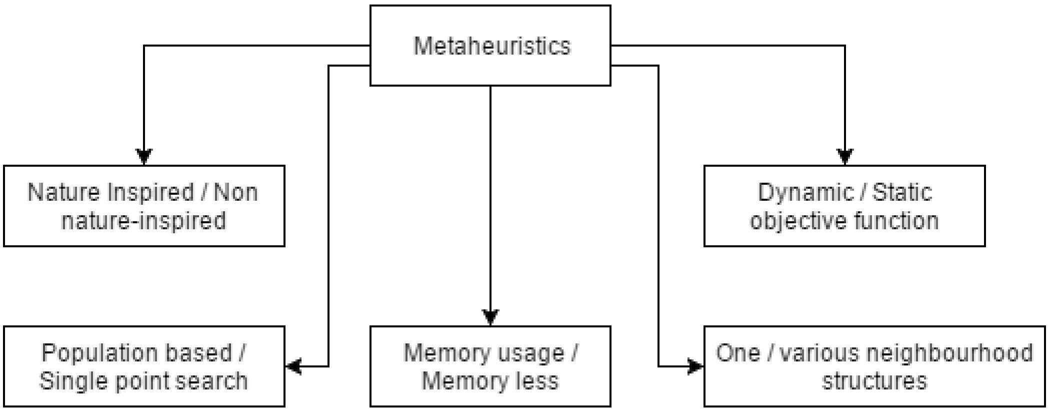


Fig. 1. Classification of metaheuristics

1.4 Algorithms

Several algorithms have been developed since the emergence of metaheuristics. A brief introduction to some of these algorithms is given below.

1. Genetic Algorithm (1970)

Genetic Algorithm, as the name suggests, is based on the phenomenon of human evolution. Darwin's theory of evolution is based on the principle of survival of the fittest. The basic idea of Genetic Algorithms is to first generate an initial population randomly which consists of individual solutions to the problem called Chromosomes, and then evolve this population after a number of iterations called Generations. During each generation, each chromosome is evaluated, using some measure of fitness. To create the next generation, new chromosomes, called offspring, are formed by either merging two chromosomes from current generation using a crossover operator or modifying a chromosome using a mutation operator. A new generation is formed by selection, according to the fitness values, some of the parents and offspring, and rejecting others so as to keep the population size constant. Fitter chromosomes have higher probabilities of being selected. After several generations, the algorithms converge to the best chromosome, which hopefully represents the optimum or sub optimal solution to the problem.

2. Simulated Annealing (1983)

Simulated Annealing, is an early Meta-heuristic algorithm originating from an analogy of how an optimal atom configuration is found in statistical mechanics. It uses temperature as an explicit strategy to guide the search. In Simulated Annealing, the solution space is usually explored by taking random tries. The Simulated Annealing procedure randomly generates a large number of possible solutions, keeping both good and bad solutions. As the simulation progresses, the requirements for replacing an existing solution or staying in the pool becomes stricter and stricter, mimicking the slow cooling of metallic annealing. Eventually, the process yields a small set of optimal solutions. Simulated Annealing advantage over other methods is its ability to obviate being trapped in local minima.

3. Tabu Search (1986)

Tabu search, is the technique that keeps track of the regions of the solution space that have already been searched in order to avoid repeating the search near these areas. It starts from a random initial solution and successively moves to one of the neighbors of the current solution. The difference of tabu search from other metaheuristic approaches is based on the notion of tabu list, which is a special short term memory. That is composed of previously visited solutions that include prohibited moves. In fact, short term memory stores only some of the attributes of solutions instead of whole solution. So it gives no permission to revisited solutions and then avoids cycling and being stuck in local optima.

Following are some new algorithms that have become popular.

4. Particle Swarm Optimisation (1995)

Particle Swarm Optimization (PSO), is a biologically inspired or natured-inspired computational search and optimization method developed by Eberhart and Kennedy in 1995 based on the natural behavior of swarms and their capabilities. On the other hand, basic PSO is more appropriate to process static, simple optimization problem. Theory of particle swarm optimization (PSO) has been growing rapidly. PSO has been used by many applications of several problems. The precise definition of PSO : "It is a global swarm algorithm which uses multiple individual particles to explore the search space to find the optimal solution ".

Basic idea for PSO optimization is came from about from watching some swarm moving together such as swarm of animal like honeybees, ants, fish etc. It not only uses a momentum of individual particle at the direction in which it is already moving but also uses an information of that particle's "previous best solution" called as personal best, p_{best}. and also the "best solution in overall population" to move this particle around in the search space (This value is called g_{best}).

5. Artificial Bee Colony Algorithm (2005)

Artificial Bee Colony (ABC) algorithm was proposed by Karaboga for optimizing numerical problems. The algorithm simulates the intelligent foraging behavior of honey bee swarms. It is a very simple, robust and population based stochastic optimization algorithm. In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. A bee waiting on the dance area for making a decision to choose a food source is called onlooker and one going to the food source visited by it before is named employed bee. The other kind of bee is scout bee that carries out random search for discovering new sources.

6. Crow Search Algorithm (2016)

Crows (crow family or corvids) are considered the most intelligent birds. They contain the largest brain relative to their body size. Crows have been known to watch other birds, observe where the other birds hide their food, and steal it once the owner leaves. If a crow has committed thievery, it will take extra precautions such as moving hiding places to avoid being a future victim. In fact, they use their own experience of having been a thief to predict the behavior of a pilferer, and can determine the safest course to protect their caches from being pilfered. CSA is based on this behaviour of crows, where the best place to hide food represents the best solution. This is a very new algorithm and has proven to be comparatively faster and more efficient than the previous ones.

Chapter 2

Algorithms Used

2. ALGORITHMS USED

2.1 Genetic Algorithm

2.1.1 Introduction

Genetic algorithm (GA) is a search method for optimal solution of given objective function inspired by the process of natural selection. Genetic Algorithms were invented to mimic some of the processes observed in natural evolution. The idea with GA is to use this power of evolution to solve optimization problems. The father of the original Genetic Algorithm was John Holland who invented it in the early 1970's. GA generates solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover.

GAs simulate the survival of the fittest among individuals over consecutive generation for solving a problem. Each individual represents a point in a search space and a possible solution. The individuals in the population are then made to go through a process of evolution.

The objective function define the cost from the expected results i.e. the error. The objective function should be defined such that the error converges to zero.

GAs are based on an analogy with the genetic structure and behaviour of chromosomes within a population of individuals using the following foundations:

- Individuals in a population compete for resources and mates.
- Those individuals most successful in each 'competition' will produce more offspring than those individuals that perform poorly.
- Genes from `good' individuals propagate throughout the population so that two good parents will sometimes produce offspring that are better than either parent.
- Thus each successive generation will become more suited to their environment.

After an initial population is randomly generated, the algorithm evolves the through three operators:

1. Selection which equates to survival of the fittest;
2. Crossover which represents mating between individuals;
3. Mutation which introduces random modifications.

2.2.2 GA Parameters

- Selection method
- crossover method
- crossover probability
- mutation method
- mutation probability
- Replacement method.

These parameter influence the domain of solution space over search space. The accuracy of solutions, global maxima search and rate of convergence for defined objective function are needed tune for fastest and most accurate result.

2.2.3 GA Pseudo-code

1. Set t = 0.

2. Randomize initial population P (0).

3. Evaluate population P (0).

4. While termination condition is not true:

    a. Evaluate fitness of each individual of P (t).

    b. Select individuals as parents from P (t) based on fitness.

    c. Apply search operators (crossover and mutation) to parents, and generate P (t + 1).

    d. Set t = t + 1.

END

2.3 Crow Search Algorithm

This algorithm is based on how crows search for food in hidden places.

The principles of CSA are listed as follows:

- Crows live in the form of flock.
- Crows memorize the position of their hiding places.
- Crows follow each other to do thievery.
- Crows protect their caches from being pilfered by a probability

It is assumed that there is a d-dimensional environment including a number of crows. The number of crows (flock size) is N and the position of crow i at time (iteration) iter in the search space is specified

And itermax is the maximum number of iterations. Each crow has a memory in which the position of its hiding place is memorized.

At iteration iter, the position of hiding place of crow i is shown by m(i,iter). This is the best position that crow i has obtained so far. Indeed, in memory of each crow the position of its best experience has been memorized. Crows move in the environment and search for better food sources (hiding places).

Assume that at iteration iter, crow j wants to visit its hiding place, m(j,iter). At this iteration, crow i decides to follow crow j to approach to the hiding place of crow j. In this case, two states may happen:

- State 1: Crow j does not know that crow i is following it. As a result, crow i will approach to the hiding place of crow j i.e. $Memory(x^{j,iter})$. In this case, the new position of crow i is obtained as follows:

  $$x^{i,iter+1} = x^{i,iter} + rand_i * flight * (Memory(x^{j,iter}) - x^{i,iter})$$

  Where $rand_i$ is a random number with uniform distribution between 0 and 1 and $flight$ denotes the flight length of crow i at iteration iter.

- State 2: Crow j knows that crow i is following it. As a result, in order to protect its cache from being pilfered, crow j will fool crow i by going to another position of the search space.

2.3.1 CSA parameters:

- Flock size(N) - number of birds(particles) randomly searching in the search space
- Flight length ($flight$) – parameter used to control the diversity of solution
- Awareness probability (AP) – the parameter which decides, the level of awareness of a bird

Each crow of flock N denotes a feasible solution in d-Dimensional space $x^n_{i=1,2,..d}$,each crow evaluates the quality(fitness) of its solution.

For each iteration a random crow is selected and is followed to locate its solution which is hidden. The selection depends upon the awareness probability. The new location is evaluated as follows

$$x^{i,iter+1} = x^{i,iter} + rand_i * flight * (Memory(x^{j,iter}) - x^{i,iter})$$

The feasibility and the fitness of new solution are evaluated. The memory of the crow is updated if

$f(x^{iter+1}) > f(x^{iter})$

Now, for every iteration the best solution is updated and compared with previous iteration's best solution. The best solution till last iteration is updated as final optimal solution.

To improve the performance of CSA for given problem we have to tune the Flight length and awareness probability.

2.3.2 Advantages of CSA

- Less number of parameters: Flight length and awareness probability. Parameter setting consumes a lot of time in GA or PSO.
- CSA is not a greedy algorithm. This increases the diversity of the solutions.
- Flight length is a parameter directly available to control the diversity of solutions.

2.2 Artificial Bee Colony Algorithm

2.2.1 Introduction

Artificial bee colony algorithm (ABC) was proposed by Karaboga in 2005 is inspired by naturally intelligent behaviour of bee colony. This algorithm is excellent example of solution through social cooperation of swarm intelligence of bees.

In the ABC algorithm, the colony of artificial bees contains three main groups of search agents:

- Employed bees
- Onlooker bees
- Scout bees

The employed bees knows the location of food source and each employed bee represent a solution in search space. The employed bees exploit the search space for possible solution and also gather information about the solution. The bees has knowledge of the position of solution in search space and profitability of the solution. They share this information with other bee of the hive.

Onlooker bee are bees waiting in hive for the employed bee to return and share their knowledge about the solution its position and quality. The onlooker then apply greedy selection algorithm to choose existing solution. Higher quality of food will have higher probability to get chosen. The local space around the solution will now be explored by the onlooker bee.

The scout bees are employed bees which had to abandon their source because of poor quality. Scout bee produces new solution for every abandoned solution by the employed bees. When a solution penalty cost override the penalty limit it is abandoned

.ABC randomly initialize the swarm population. The solution vector $x_j = \{x_1, x_2, .. x_d\}$ for D-dimensional problem space. The new solution are generated around these solution are as follow

$$x_{i+1,j} = x_{i,j} + \varphi_i.(x_{i,j} - x_{k,j})$$

$$\varphi\_i \ \ is\ the\ random\ generated\ over\ uniform\ distribution\ [-1,1]$$

If the fitness value of new solution is better than the one in memory of bee then the memory of location is updated to new generated solution or memory is not updated. After fitness of all employed bee. An onlooker bee evaluates the food information taken from all employed bees and chooses a food source with a probability related to its quality. This selection is really a roulette wheel probabilistic selection mechanism. If the quality of food is not improved over predefined penalty the solution is abandoned and new random solution is created.

2.2.2 ABC pseudo-code

1. Set t = 0.
2. Randomize initial population P (0).
3. Repeat:
   a. For employed bee:
      i. Produce new position P(i)
      ii. Evaluate cost function value C(i)
      Iii. Update position
   b. Calculate fitness f(i) and probability P(i)
   c. For onlooker bee:
      i. Select a solution z(i) depending on f(i)
      ii. Produce new solution
      iii. Evaluate cost function value C(i)
      iv. Update position
   d. Solution with poor cost are abandoned depending on penalty
   e. New solution is randomized for abandon bee

Until Max Iteration

2.2.3 Control parameters

- Colony size
- Acceleration constant

Chapter 3

Estimation of Signal parameters

3. ESTIMATION OF SIGNAL PARAMETERS

3.1 Introduction

Parameter estimation refer to collecting of sampled data and estimating the parameters on which sampled data depends. The measurable quantities in a system are the function of certain parameters for a given system. The value of these parameters represent the state of system at any given instant. The output characteristic of system is a function of all or some parameter. So, estimating the parameter from the measured value is important to predict the behaviour of the system.

The function of characteristics of system and parameters ranges from straight line equation, curves, exponential and differential equations. Differential equation are dominant in these. In electrical system, higher order differential equation are present for the estimation of the parameters. The solution of theses differential equation using analytical approach require a huge computational resources, time consuming and many times the solutions can’t be found because the inadequacies of the resources at hand. Finding out the solution of these differential equation involves complex calculation resulting in cumbersome time. Thus, a unique approach to these problem is required, these approach should use less resources also should have simple approach for solutions in search space.

Metaheuristic approach is new approach inspired by the nature, which primarily depends randomness in behaviour of nature. The solutions is inspired by the characteristic of the natural system and their swarm intelligence. The application of metaheuristic algorithm for finding the solution of problem involving complex function turns the problem to a simple random shooting problem, searching around the possible solution to find the optimal. All the feasible solution in problem domain is known as search space. The approach is characteristic by the

1. Randomness solutions throughout the search space.
2. Aim and shooting around the best apparent solution
3. New solutions are distributed over search space according the distribution characteristic of natural system in considerate.

This way metaheuristic approach randomly guesses the solution for given formulated problem. The generated solutions are the parameter of the system, then the output is evaluated with these parameter, thus the error between the calculated and measured output is error term. This error is the heuristic also known as the objective function for the algorithm. The algorithm tries to minimize the error by generating new solution with better heuristic or less with minimal error.

The solution space around the current population best is explored. Hence a global maxima is obtained and also the computation time is largely reduced as the problem is converted to linear form of parameter estimation. Also, the multi-dimensional search space is generated according the problem. A solution vector contains all the parameter to be estimated, multiple parameter can be estimated at same time. Thus, the multi-dimensional problem is solved for all parameters every iteration. The search space is characteristic of the upper and lower limit of the parameter.

To test the metaheuristic approach for the parameter estimation, the simple problem chosen is voltage signal parameter estimation. The algorithm is provided the measured signal values of any system. The algorithm randomly generate the possible solution in search space and the parameters of signal are estimated

Problem formulation

The signal considered is voltage signal. Alternating voltage in our AC system is the function of Amplitude, Frequency and Phase. These parameter once known are the basic parameter for all the following evaluation of system like load flow, losses estimation etc.

$$V = V_{max} \times \sin(2 \times pi \ \times f \times t + \emptyset).$$

The voltage parameters are $Vmax, f$, $\emptyset$. $Vmax$, f is estimation directly from the Voltage measured through PT. This sampled data cannot be used for $\emptyset$ estimation as it requires a reference.If the reference is available in system then the phase can also be estimated.

The problem formulated is provided with measured voltage which is simulated

$$V = A_i \times \sin(2 \times pi \ \times f_i \times t + \emptyset_i)_{i=1,2,3}$$

For various value of A, f, phase the voltage at sampling instant is provided. Also a reference voltage sampled point is also given, the reference is considered at zero angle

$$V_{ref} = A_{ref} \times \sin(2 \times pi \times f \times t).$$

The problem dimension is three. The solution vector is x dimension size is same as the number of parameters to be estimated, individual parameter is represented as $x(\mathrm{j})_{1,2\ldots pd}$.

The objective function for the proposed problem is formulated. This function represent error as function of the parameters with the error minimizing as the estimated parameter tends to their actual value. The objective formulated for proposed problem

$$V_{cal} = x(1) * \sin(2 * pi * x(2) * t + x(3))$$

$$error = (V_{measured} - V_{cal})$$

The algorithm implemented to solve the proposed problem are CSA. For CSA the parameter were set as

Flock size (N) =50; Awareness probability=0.1;

Flight length=3; Maximum Iterations=500;

3.2 Proposed Algorithm for Voltage signal parameter estimation

The proposed algorithm to estimate the voltage parameter is presented below.

1. Sampled data of voltage at point is supplied.
2. Randomly initialize voltage parameters A, f and $\emptyset$.
3. Error between measured and calculated values of voltage is used as fitness function
4. Fitness is evaluated for all population size.
5. CSA parameter are set AP, fl, N, Itermax.
6. Lowest value of error in each generation and corresponding voltage parameters are stored
7. After Max iteration the best fitness value and its corresponding parameter are return.

Chapter 4

Estimation of fault location on transmission line

4. ESTIMATION OF FAULT LOCATION ON TRANSMISSION LINE

4.1 Types of Faults

Electrical fault is the departure of voltages and currents from nominal values or states. Under normal operating conditions, power system equipment or lines carry normal voltages and currents which results in a safer operation of the system.

But when fault occurs, it causes excessively high currents to flow which causes the damage to equipment’s and devices. Fault detection and analysis is necessary to select or design suitable switchgear equipment’s, electromechanical relays, circuit breakers and other protection devices.

There are mainly two types of faults in the electrical power system. Those are symmetrical and unsymmetrical faults.

1. **Symmetrical faults**

   These are very severe faults and occur infrequently in the power systems. These are also called as balanced faults and are of two types namely line to line to line to ground (L-L-L-G) and line to line to line (L-L-L).
   Only 2-5 percent of system faults are symmetrical faults. If these faults occur, system remains balanced but results in severe damage to the electrical power system equipment’s.

   Above figure shows two types of three phase symmetrical faults. Analysis of these fault is easy and usually carried by per phase basis. Three phase fault analysis or information is required for selecting set-phase relays, rupturing capacity of the circuit breakers and rating of the protective switchgear.

2. **Unsymmetrical faults**

   These are very common and less severe than symmetrical faults. There are mainly three types namely line to ground (L-G), line to line (L-L) and double line to ground (LL-G) faults.

Line to ground fault (L-G) is most common fault and 65-70 percent of faults are of this type.

It causes the conductor to make contact with earth or ground. 15 to 20 percent of faults are double line to ground and causes the two conductors to make contact with ground. Line to line faults occur when two conductors make contact with each other mainly while swinging of lines due to winds and 5- 10 percent of the faults are of this type.

These are also called unbalanced faults since their occurrence causes unbalance in the system. Unbalance of the system means that that impedance values are different in each phase causing unbalance current to flow in the phases. These are more difficult to analyse and are carried by per phase basis similar to three phase balanced faults.

Whenever a fault occurs on a transmission line, it is to be isolated by protective relays. During this period the entire grid will be under stress. So the maintenance crew should identify the faulted component and repair any damages done for quick restoration of line [1].

There is a requirement of swift and accurate fault location to maintain the power system operation and stability.

The following categorization can be made for various algorithms developed for fault location estimation:

1. **Single-end** – uses voltage and current measurements from one terminal of the line
2. **Double-end** –uses either synchronised or unsynchronised measurements from both line ends
3. **Multi-end -** uses either synchronised or unsynchronised measurements from many different line ends
4. **Wide-area methods -** some of the network terminals are equipped with measurement devices and network equations are employed to estimate fault location by limited measurements

For the purpose of this project, single-end method has been used. Though this method has less accuracy as compared to the other three, but it is simpler to implement and test newer algorithms like Crow search and Artificial Bee Colony algorithms.

A large number of fault location algorithms have been developed and proposed over the years. These algorithms can be divided into

1. those using differential equations of transmission line and estimating line parameters [3]
2. those extracting fundamental frequency current and voltage phasors to compute fault location [2]
3. those based on traveling wave (TW) theory [5-13]

Also artificial intelligence techniques such as neural networks and support vector machines have found applications in locating a fault on transmission line.

This project aims to implement fault location estimation using meta-heuristic algorithms/ various nature based algorithms.

First population based Genetic algorithm is used to test working of the transmission line models created. Once the testing has been done, swarm intelligence algorithms like ABC and CSA are used to further optimize the values from a pi section transmission line model.

4.2 Mathematical Modelling of Transmission Line

1. R-L series Model

For the purpose of testing we have considered a simple series R-L transmission line model, for parameter estimation.

Applying Kirchhoff's Voltage law around the loop we get:

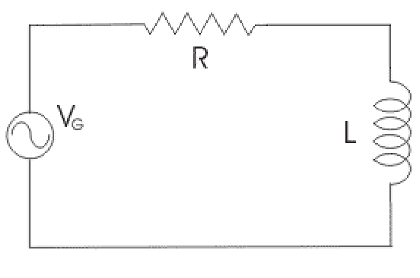


Fig. 4.1 Series RL model

$$V_i = \mathrm{R} * I_i + L * \frac{dI}{dt}$$

Now for time t = t_i

$$\left.\frac{dI}{dt}\right|_{t=t_i} = \frac{I_{i+1} - I_{i-1}}{2\Delta t}$$

Substituting 2 in 1 we get

$$V_i = \mathrm{R} * I_i + L * \frac{I_{i+1} - I_{i-1}}{2\Delta t}$$

This value of voltage is to be used for the evaluation of fitness function and optimization of parameters for error reduction.

2. **Pi-section Model**

   Actual transmission line model, to estimate fault location using R and L values obtained from metaheuristic methods.

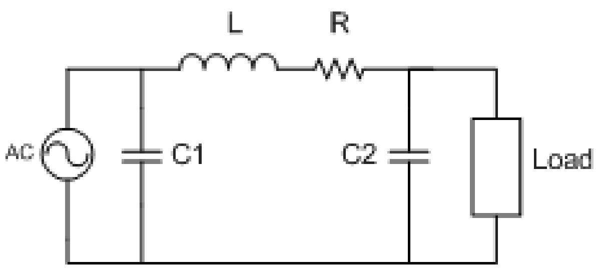


Fig. 4.2 Pi Section model

Here a single pi-section model has been considered with

C_1=C_2=C

Applying Kirchhoff's Voltage law around the loop we get:

$$v = \mathrm{r} * I + L * \frac{dI}{dt} + RC * \frac{dv}{dt} - LC * \frac{d^2v}{dt^2}$$

Now for time t = t_i

$$\left.\frac{dv}{dt}\right|_{t=t_i} = \frac{v_{i+1} - v_{i-1}}{2\Delta t}$$

$$\left.\frac{dI}{dt}\right|_{t=t_i} = \frac{I_{i+1} - I_{i-1}}{2\Delta t}$$

$$\left.\frac{d^2v}{dt^2}\right|_{t=t_i} = \frac{v_{i+1} - 2v_i + v_{i-1}}{\Delta t^2}$$

Substituting the above,

$$v_i = r * I_i + L * \frac{I_{i+1} - I_{i-1}}{2\Delta t} + RC * \frac{v_{i+1} - v_{i-1}}{2\Delta t} - LC * \frac{v_{i+1} - 2v_i + v_{i-1}}{\Delta t^2}$$

This value of voltage is to be used for the evaluation of fitness function and optimization of parameters for error reduction.

4.3 Simulink Model of Transmission Line

The Simulink model along with the corresponding line parameters have been mentioned below:

1. **R-L series Model**

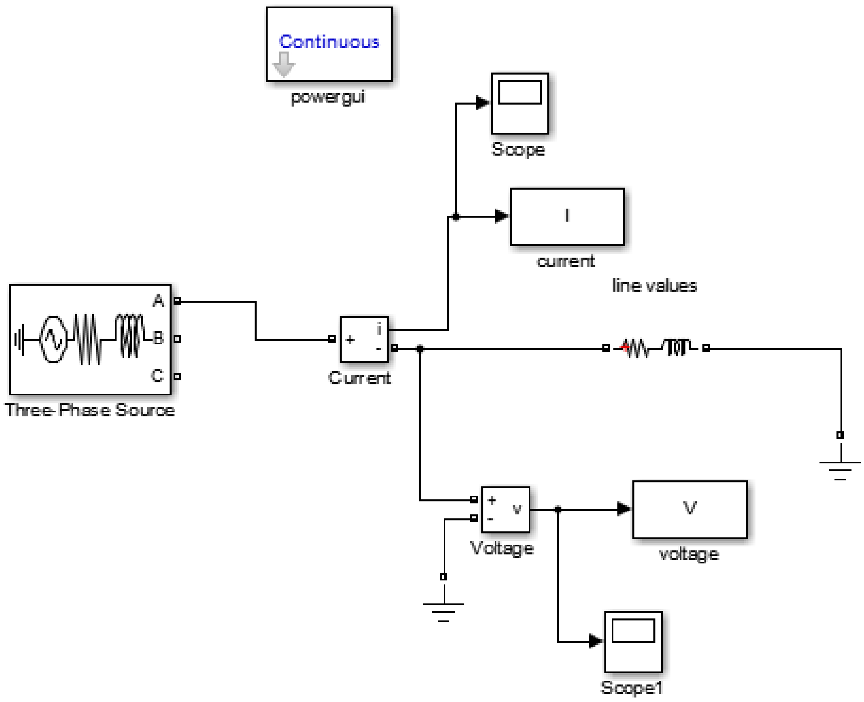


Fig. 4.3 Simulink model for series RL circuit

2. **Pi-section Model**

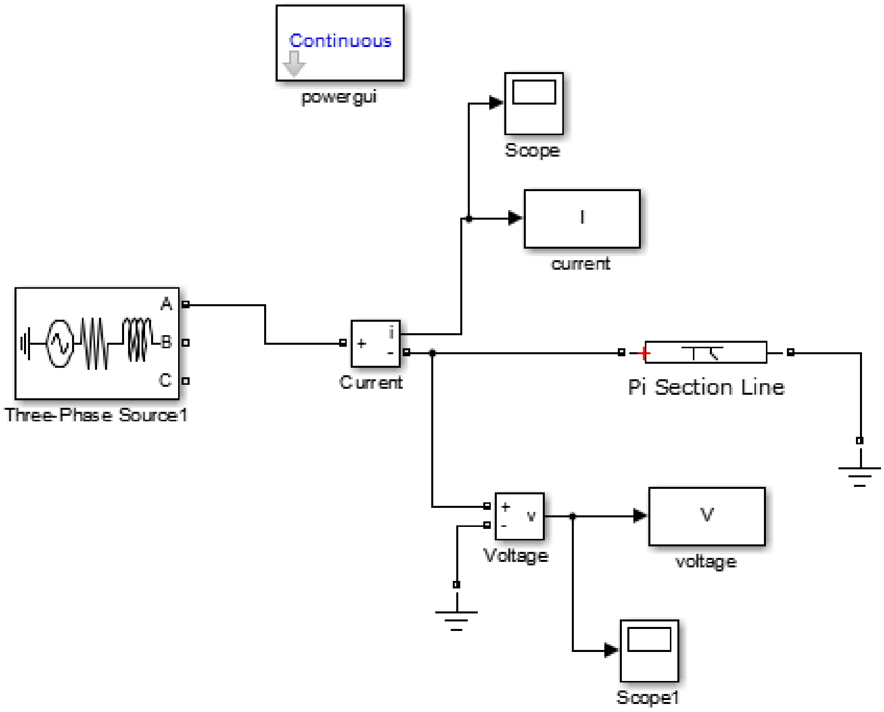


Fig. 4.4 Simulink model for Pi section

The values considered for this model are

$r = 0.05\ \Omega/\text{km}$ $\quad$ $l = 0.001$ H/km

$c = 19.74\text{e-}9$ F/km $\quad$ $T_L = 400$km

4.4 Proposed Algorithm for Fault Location

The proposed algorithm to estimate the distance to the fault is presented below.

1. Simulink model of transmission line involving a single line to ground fault is built
2. Obtain and store voltage and current values at transmission line end using Simulink
3. Randomly initialize transmission line parameters R, L and C
4. Swarm population and maximum number of iterations is set
5. Error between measured and calculated values of voltage is used as fitness function
6. Fitness at each random value of R,L and C is calculated
7. Lowest value of error in each generation and corresponding line parameters are stored
8. Continue step 5 to 7 till maximum number of generations is reached
9. Using the estimated value of R_{cal} and L_{cal}, calculate the location of fault using set R/km and L/km values

Chapter 5

Maximum Power Point Tracking of Photo Voltaic

5. MAXIMUM POWER POINT TRACKING OF PHOTO VOLTAIC (PV)

5.1 Working of Solar Cell

Each solar cell in the Photo Voltaic panel consists of a p-n diode. On combination, free electrons are diffused in the p-type region resulting in a positive charge in the n-type region and a negative charge in the p-type region. This electric field creates a potential barrier for further flow. Due to incident radiation, electron hole pairs are generated due to photoelectric effect. The electric field previously generated thus sends the electrons towards the n-type region and the holes towards the p-type region. Thus, sufficient voltage is generated across the cell. In a PV panel, in order to obtain the desired voltage and power, several cells are connected in series and parallel.

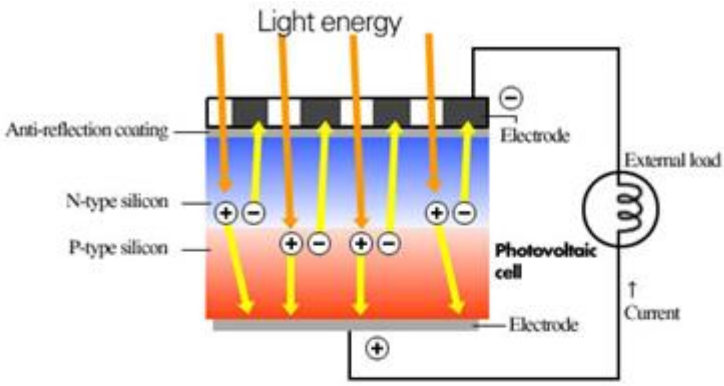


Fig. 5.1 Working of Solar cell

5.2 Equivalent Circuit Diagram of Solar Cell

An ideal solar cell can be modelled as a current source in parallel with a diode. In the absence of light it behaves as a diode. As the incident light intensity increases the current increases as shown in figure 2.

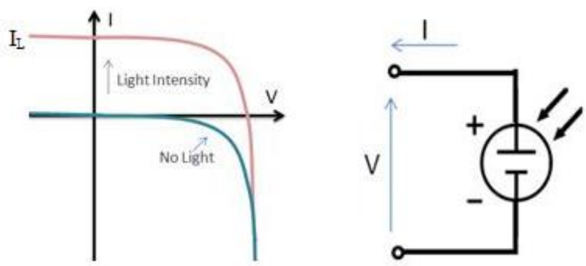


Fig. 5.2 Increase in current with light intensity

However due to its non-ideal nature we have to account for parasitic resistances:

1. R_S: Series Resistance, which is because of contact resistance between metal contact and the silicon and resistance to the flow of current between the emitter and base.
2. R_{SH}: Shunt resistance, which is due to the non-ideal nature of the p-n junction and the presence of impurities near the edge of the cell that provide a short circuit path around the junction.

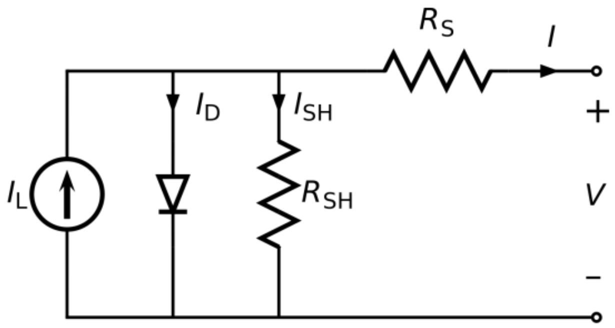


Fig. 5.3 Equivalent Circuit Diagram of Solar cell

We can then express the output current as,

$$I = I_L - I_D - I_{SH}$$

where,
I is solar cell output current,
I_D is the diode current and
I_{SH} is the current through shunt resistance
I_L is the photo generated current

The diode current I_D is given by $I_D = I_s\left(e^{\frac{V+R_S*I}{nKT}} - 1\right)$

where,
I_s is the dark saturation current (diode leakage current in absence of light)
q is the electron charge
n is the diode ideality factor(manufacturing value, between 1 and 2)
K is Boltzmann’s constant

The current through the shunt resistance R_{SH} is expressed as

$$I_{SH} = \frac{V + I * R_s}{R_{SH}}$$

Thus, the output current can be given by,

$$I = I_L - I_s\left(e^{\frac{V+R_S*I}{nKT}} - 1\right) - \frac{V + I * R_s}{R_{SH}}$$

This gives the V-I characteristics as shown in Fig. 5.4.

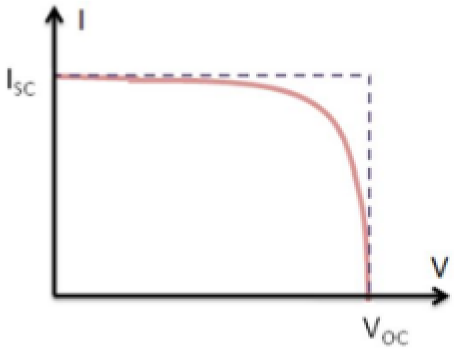


Fig. 5.4 V-I Characteristics of PV

From the Fig., we can determine the open circuit voltage when output current is zero.

The open circuit voltage is given by $Voc\ =\ \left(\frac{nkT}{q}\right) ln\left(\frac{I_L}{I}\ +\ 1\right)$.

The short circuit current is the total photo generated current and is given by $I_{SC} = I_L$.

Maximum Power Point

We can see that the power is zero when the current is maximum (I_{SC}) as well as when the voltage is maximum (Voc). Thus there exists an intermediate point at which the power from the solar cell is maximum. The current and voltage at this point is denoted by I_{MP} and V_{MP}. While harnessing power from PV it is desired that the system operates at this Maximum Power Point irrespective of the load conditions.

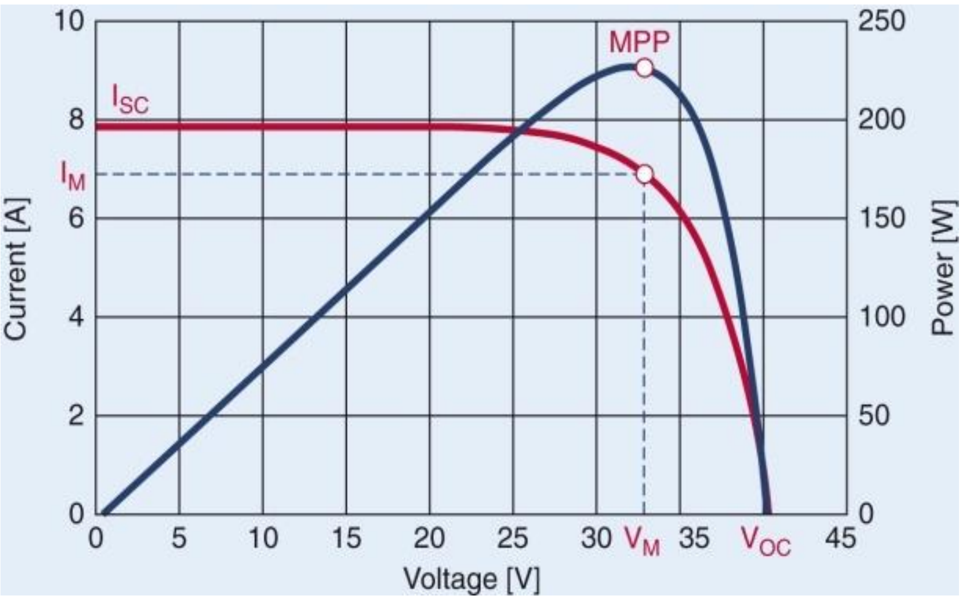


Fig. 5.5 Maximum Power Point (MPP) of PV

5.3 Fill Factor

It determines the quality of the solar cell by comparing the theoretical maximum power to the practical maximum power. The I-V characteristics are desired to the more rectangular.

$$FF = \frac{I_{MPP} * V_{MPP}}{I_{SC} * Voc}$$

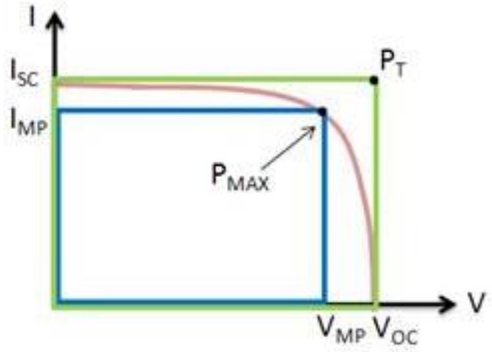


Fig. 5.6 Fill Factor of PV

5.4 Efficiency

The input power to the PV is considered to be the product of incident radiation (in W/m^2) and the total area.

$$\eta = \frac{P_{out}}{P_{in}}$$

5.5 Effect of Irradiation and Temperature

As irradiation increases, the photo generated current increases. Thus I_{sc} increases. V_{oc} doesn't increases much as the relationship is logarithmic.

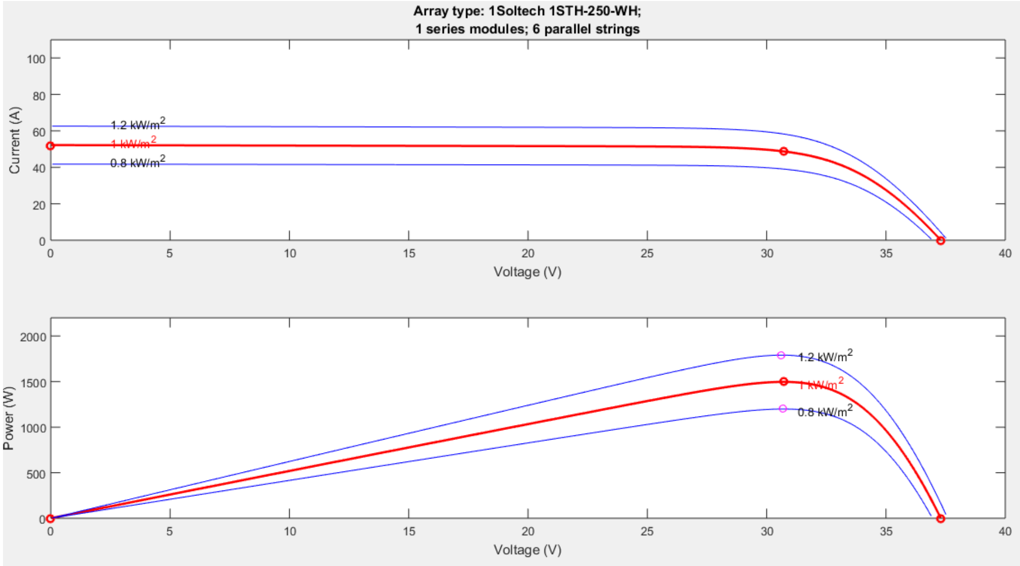


Fig. 5.6 Effect of Irradiation on PV Characteristics

V_{oc} is affected due to temperature change. With increase in temperature, the voltage decreases. The current of panel increases by a very small amount, which does not compensate the voltage drop. Hence, the output power also decreases.

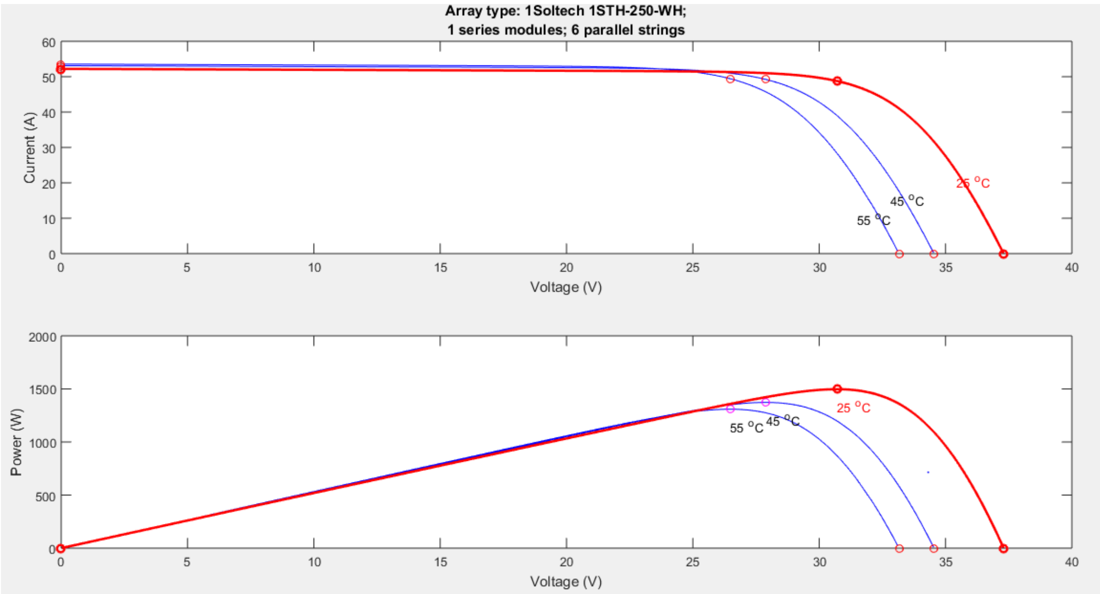


Fig. 5.7 Effect of Temperature on PV Characteristics

5.6 DC-DC Cuk Converter

In order to extract maximum power from the PV at any condition it is important to operate it at the Maximum Power Point (MPP) for the given irradiance and temperature. The dc-dc converter has to interface the PV panel and drive the operating point towards the MPP.

The operating point of a PV connected to a single resistive load is the intersection of the I-V characteristic graph with the load line ($slope = \frac{1}{R_{load}}$). The interfacing dc-dc converter has the ability to change the apparent input side impedance (R_i) so that the intersection point of the load line is at the MPP. Thus the converter operates such that, $R_i = R_{MPP}$.

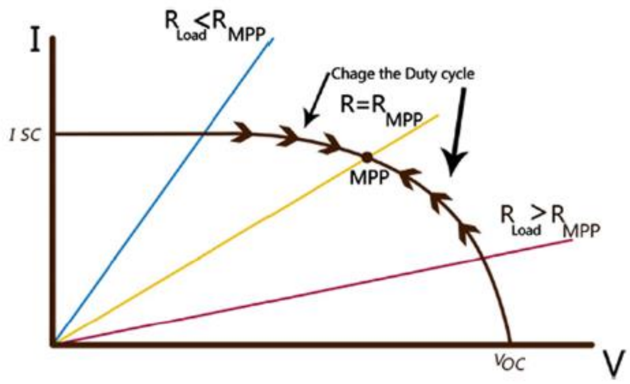


Fig. 5.8 Operating region on the I-V curve using Cuk Converter

For a cuk converter, $Ri = R_{load} * \frac{1-D^2}{D^2}$

Thus, the cuk converter can increase or decrease R_i to track R_{MPP}, by changing the duty cycle. This is one of the advantages of cuk converter that, R_i can be made greater or smaller than R_{load} so that entire operating space from open circuit voltage to short circuit current can be traversed unlike in case of buck or boost converters which have non-operating regions as V_o and R_i can only be decreased or increased respectively.

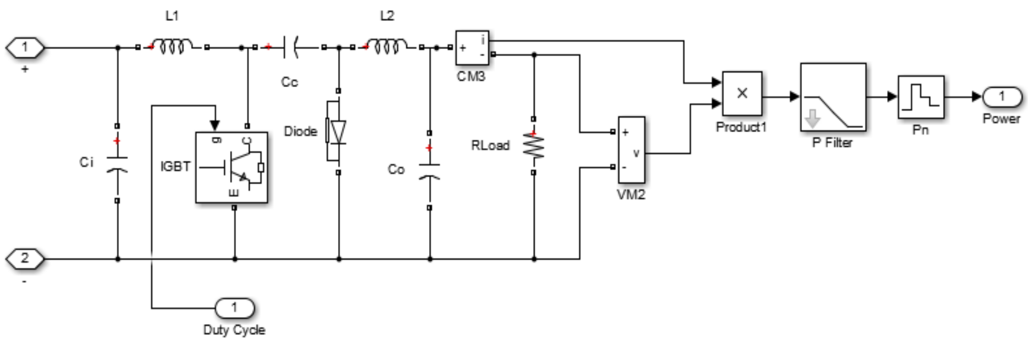


Fig. 5.9 Simulink model of Cuk Converter

5.7 Calculation of parameters for the cuk converter

The parameters are designed for an optimal condition of Irradiation= $1000W/m^2$ and Temperature=25 deg. At these conditions, PV maximum power is 250 W with I_{MPP}=8 A and V_{MPP}=30V. At these conditions optimal duty cycle is obtained to be about 0.35. Allowable ripple in currents is taken to be 5% and in V_{cc} to be 10%. Switching frequency is 10 KHz. With these conditions, parameters are calculated as follows:

$$L_1 = \frac{Vo * (1 - D) * T}{\Delta I_{L1}} \simeq 2.6 * 10^{-3}\mathrm{H}$$

$$L_2 = \frac{Vo * (1 - D) * T}{\Delta I_{L2}} \simeq 1.5 * 10^{-3}\mathrm{H}$$

$$C_c \gg \frac{Io * D * T}{\Delta V_{Cc}} \simeq 1 * 10^{-4}\mathrm{F}$$

$$C_o = \frac{\Delta I_{L2}}{\Delta Vo * 8 * fs} \simeq 1.1 * 10^{-4}$$

5.8 Maximum Power Point Tracking using Crow Search Algorithm

The proposed system tries to find the optimum duty cycle to drive the system towards MPP using the crow search algorithm. A flock of crows having memory locations as a set of randomly generated duty cycles (0<d<1) is created. The population dimension (pd) is thus equal to one. $pd = 1$.

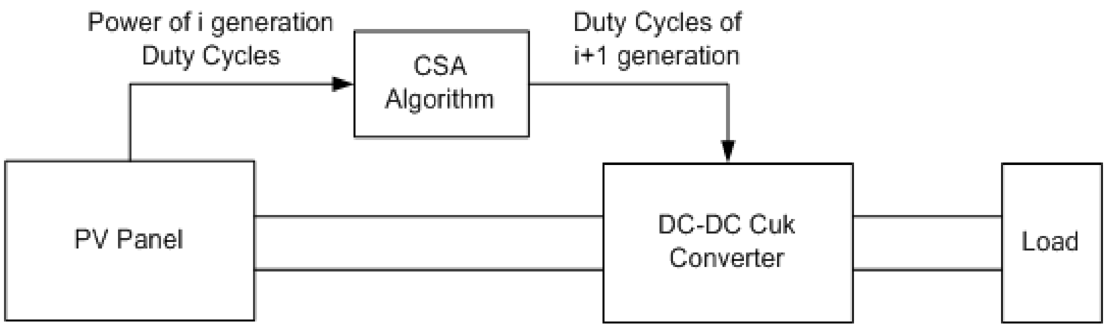


Fig. 5.10 Schematic of Proposed Scheme

The Simulink model then acts like the objective function wherein each duty cycle is tested and assigned a fitness value equal to the PV output power obtained. Thus i^{th} iteration duty cycles (X_i) are assigned fitness values (P_i). They are included in the memory if the fitness value has increased, i.e. if $P_i > P_{i-1}$

The i^{th} iteration duty cycles then produce the $i+1^{th}$ iteration duty cycles according to the crow search algorithm.

$$x^{i,iter+1} = x^{i,iter} + rand_i * flight * (Memory(x^{j,iter}) - x^{i,iter})$$

$$i = 1,2,3 \ldots N$$

Where, N denotes the flock size.

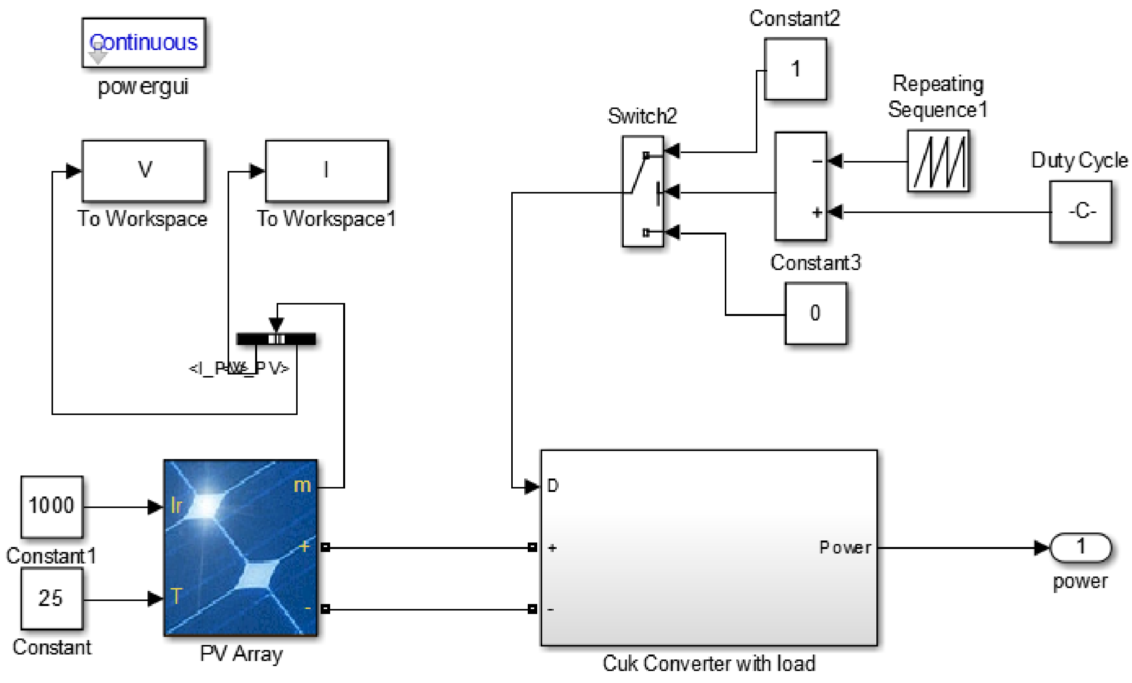


Fig. 5.11 Simulink model of system

Chapter 6

Results and Conclusions

6. RESULTS AND CONCLUSION

6.1 Estimation of voltage parameters

Parameters	Actual	Calculated	% Error
Amplitude (V)	230	230	0
Frequency (Hz)	50	49.99	0.0022
Phase (rad)	0	0.000026	-
Amplitude (V)	110	109.99	0.0051
Frequency (Hz)	55	55	0.0077
Phase (rad)	2.2	2.18	0.789
Amplitude (V)	230	230	0.0036
Frequency (Hz)	60	59.99	0.0024
Phase (rad)	1.69	1.68	0.5221

Table 6.1 Voltage parameter estimation using CSA

6.2 Estimation of fault location on Transmission Line

6.2.1 Parameter Estimation on RL series transmission line:

R_{given} (Ω)	L_{given} (H)	R_{calc} (Ω)	L_{cal} (H)	% Error R	% Error L
20	0.83	20	0.8872	0	0.286
10	0.05	10	0.0534	0	0.034
30	0.4	30	0.4276	0	0.092
50	0.002	50	0.0021	0	0.0002

Table 6.2 RL Series line parameter estimation

As it can be seen from the above table, the value of line parameter R is estimated with accuracy of 100% and error in estimation of L is also less than 1%. So the developed metaheuristic method can reliably be used for fault location estimation on a Pi section transmission line.

6.2.2 Fault Location Estimation on Pi section transmission line

Here the length of transmission line is considered to be 400km.

$r = 0.05$ Ω /km

$l = 0.001$ H/km

6.2.2.1 Varying angle of inception

Angle of inception	z (Ω /km)	R_{cal} (Ω)	L_{cal} (H)	Z_{cal} (H)	FL_g (km)	FL_C (km)	T_l (km)	% Error in Fault Location
0˚	0.31824	5.0358	0.1075	34.159	100	107.338	400	1.83442
45˚	0.31824	5.0876	0.1076	34.198	100	107.459	400	1.86487
90˚	0.31824	5.0524	0.1077	34.224	100	107.541	400	1.88519
135˚	0.31824	5.09	0.1076	34.198	100	107.461	400	1.86515

Table 6.3 Results after varying angle of inception of fault

6.2.2.2 Varying fault resistance

z (Ω /km)	R_f (Ω)	R_{cal} (Ω)	L_{cal} (H)	Z_{cal} (H)	FL_g (km)	FL_C (km)	T_l (km)	% Error in Fault Location
0.3182381	0.001	2.5646	0.0531	16.88448	50	53.05611	400	0.358
0.3182381	0.005	2.5687	0.0531	16.8851	50	53.05807	400	0.7645173
0.3182381	0.01	2.574	0.0531	16.88591	50	53.06061	400	0.7651514
0.3182381	0.05	2.615	0.0531	16.89221	50	53.0804	400	0.7700993
0.3182381	0.1	2.6664	0.0531	16.90024	50	53.10564	400	0.77641
0.3182381	1	3.5893	0.0532	17.10092	50	53.73624	400	0.9340596
0.3182381	5	7.6216	0.0543	18.6903	50	58.73055	400	2.1826386

Table 6.4 Results after varying fault resistance

6.2.2.3 Varying fault location using CSA

z (Ω /km)	R_{cal} (Ω)	L_{cal} (H)	Z_{cal} (H)	FL_g (km)	FL_C (km)	T_l (km)	% Error in Fault Location
0.3182381	8.099	0.1705	54.1943	157	170.2948	400	3.3237
0.3182381	2.5063	0.0535	17.00005	50	53.41928	400	0.85482
0.3182381	3.7786	0.0805	25.58061	75	80.38199	400	1.3455
0.3182381	5.0358	0.1075	34.15895	100	107.3377	400	0.358
0.3182381	6.3768	0.135	42.9051	125	134.8207	400	2.45518
0.3182381	7.7059	0.1626	51.68059	150	162.396	400	3.09899
0.3182381	9.1053	0.1907	60.62199	175	190.4925	400	3.87313

Table 6.5 Results after varying fault location

Following are the results of fault location using Artificial Bee Colony algorithm.

6.2.3 Varying fault Location using ABC

z (Ω /km)	R_{cal} (Ω)	L_{cal} (H)	Z_{cal} (H)	FL_g (km)	FL_C (km)	T_l (km)	% Error in Fault Location
0.3182381	2.5087	0.0535	17.00041	50	53.42039	400	0.358
0.3182381	3.7804	0.0805	25.58088	75	80.38282	400	1.34571
0.3182381	5.0359	0.1075	34.15896	100	107.3377	400	1.83444
0.3182381	6.3769	0.135	42.90511	125	134.8208	400	2.45519
0.3182381	7.7132	0.1626	51.68167	150	162.3994	400	3.09984

Table 6.6 Results after varying fault location using ABC

6.3 Maximum Power Point Tracking using CSA

Four conditions of irradiation and temperature are considered and it is checked whether the duty cycle obtained from the CSA drives the system to MPP.

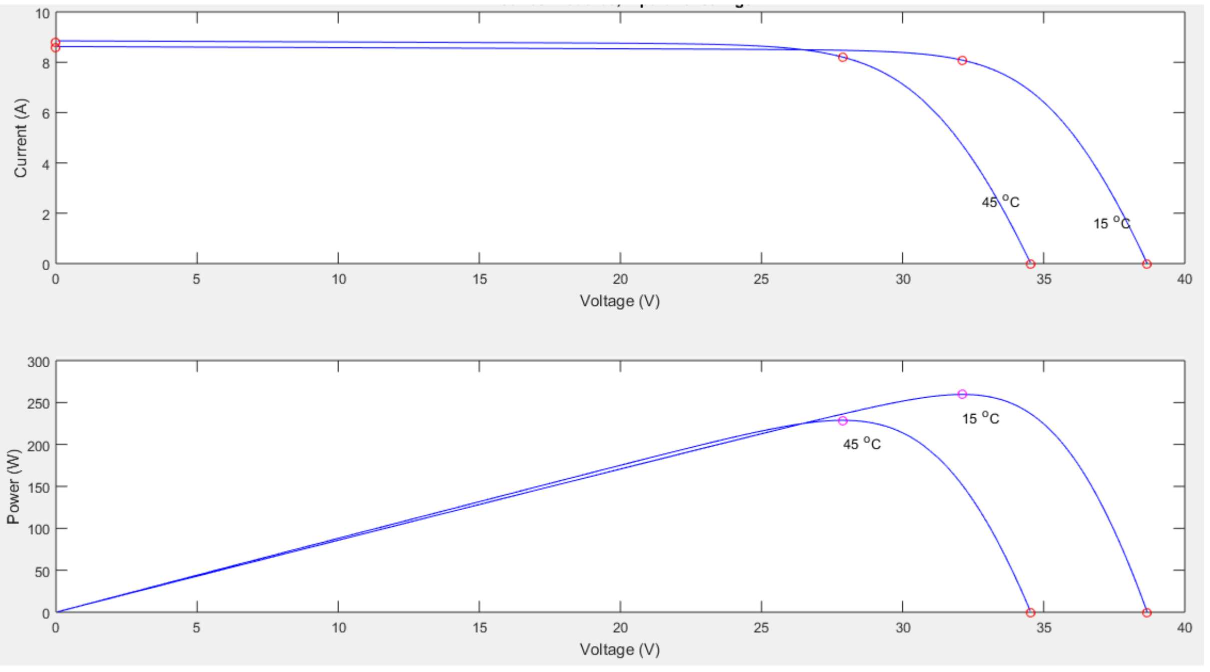


Fig. 6.1 PV Characteristics for 1000W/m² & 15, 45 deg C.

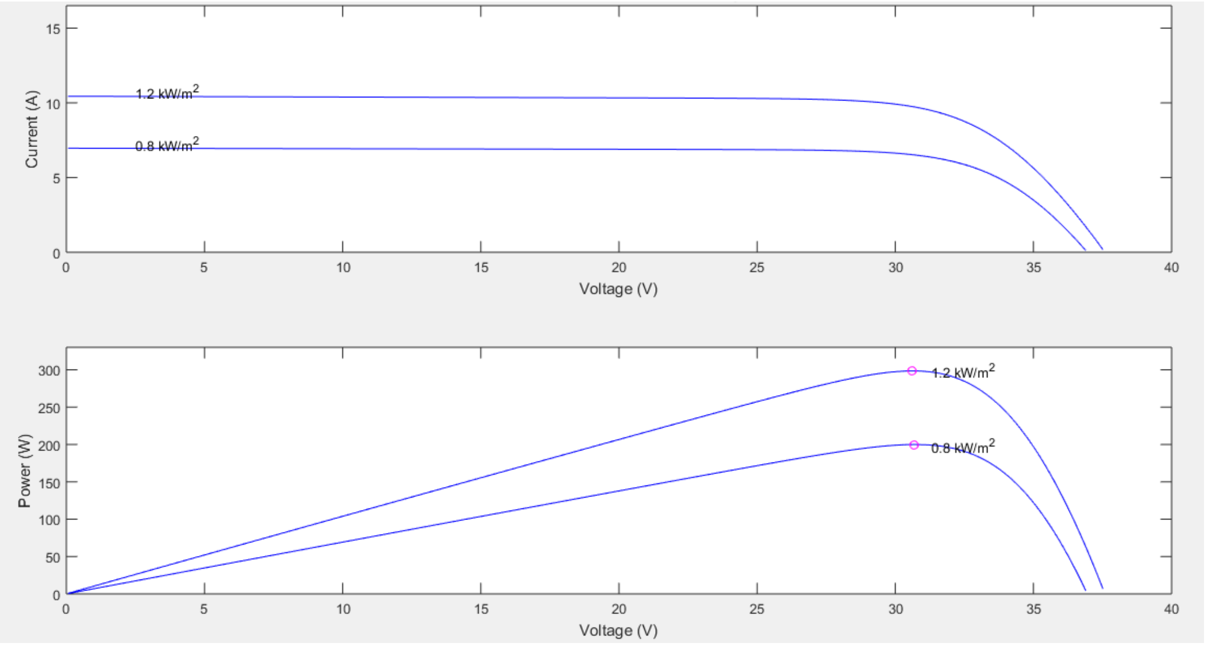


Fig. 6.2 PV Characteristics for 25 deg C & 1200, 800 W/m²

Case	Irradiation (W/m²)	Temperature (˚C)	I_{MPP}(A)	V_{MPP} (V)	P_{MPP} (W)
1	1000	15	8.087	32.11	259.6
2	1000	45	8.201	27.89	228.8
3	1200	25	10.44	30.62	298.4
4	800	25	6.515	30.68	199.9

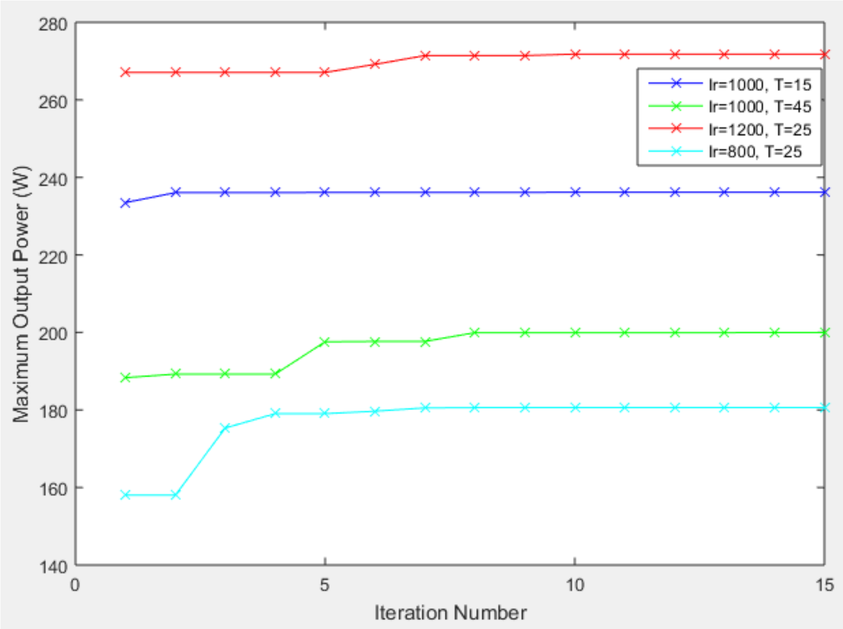
Table 6.7 MPP Characteristics of given conditions

Results obtained:

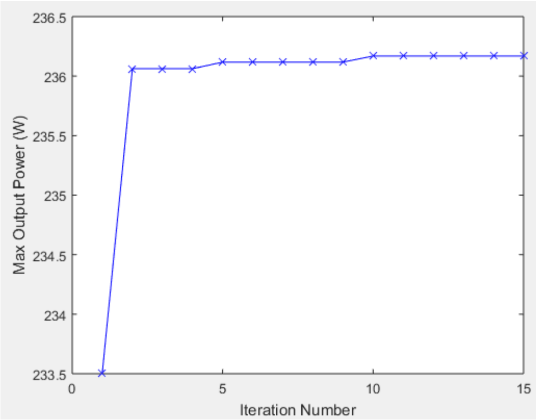
Case	Irradiation (W/m²)	Temperature (˚C)	Duty Cycle
1	1000	15	0.4689
2	1000	45	0.487
3	1200	25	0.4969
4	800	25	0.445

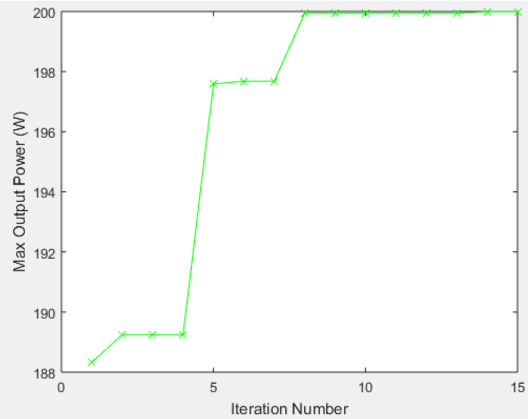
Table 6.8 Results obtained from CSA

The following graph plots the maximum power at every iteration for each case showing how the solution converges over the iterations.

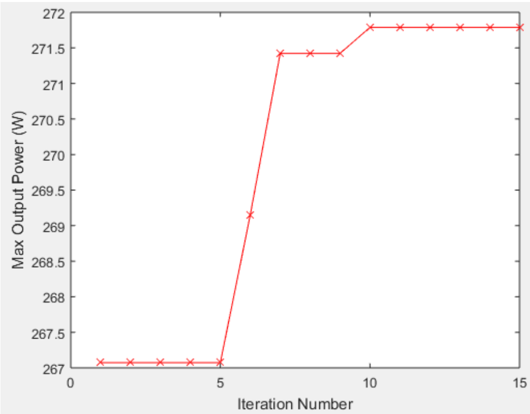


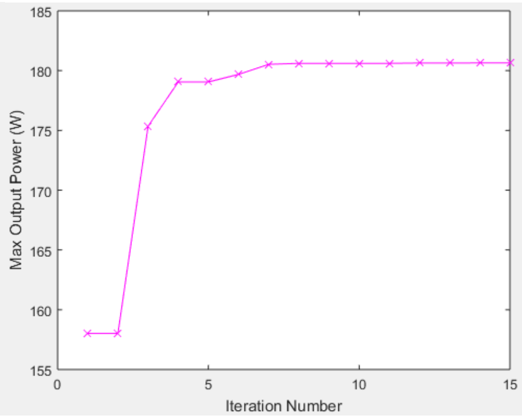
(a)





(b) (c)





(d) (e)

Fig. 6.3 (a) Variation of maximum output power vs. iterations. (b) Case 1 (c) Case 2 (d) Case 3 (e) Case 4

The obtained duty cycles for each condition are then given to the system and the PV voltage, current and power are plotted to see how closely they comply with the MPP. Fig. 1,2,3,4 show the obtained PV voltage, current and output power when the optimum duty cycle for each of the 4 conditions given above is given to the system.

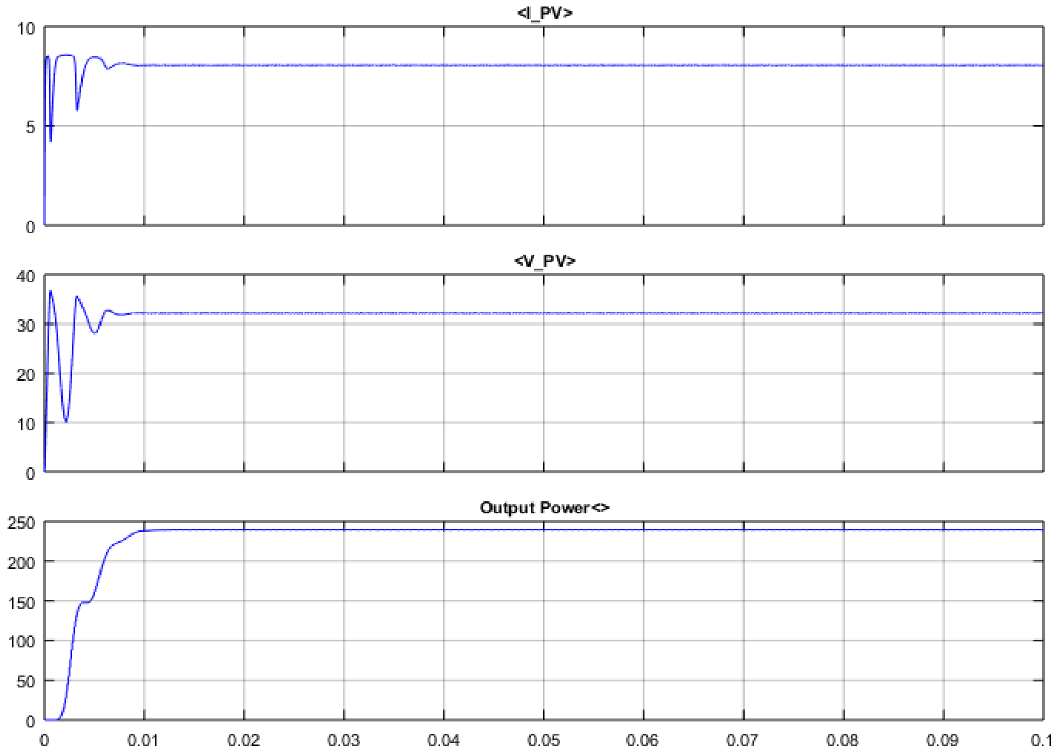


Fig. 6.4 Case 1 Simulated Parameters wrt Time

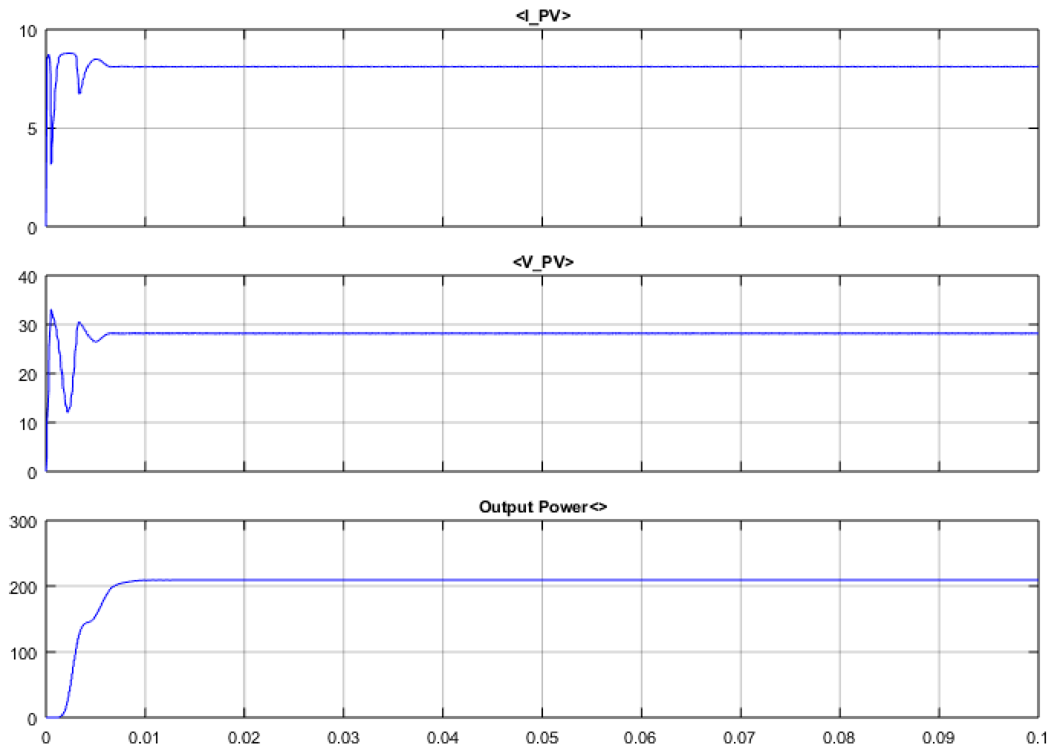


Fig. 6.5 Case 2 Simulated Parameters wrt Time

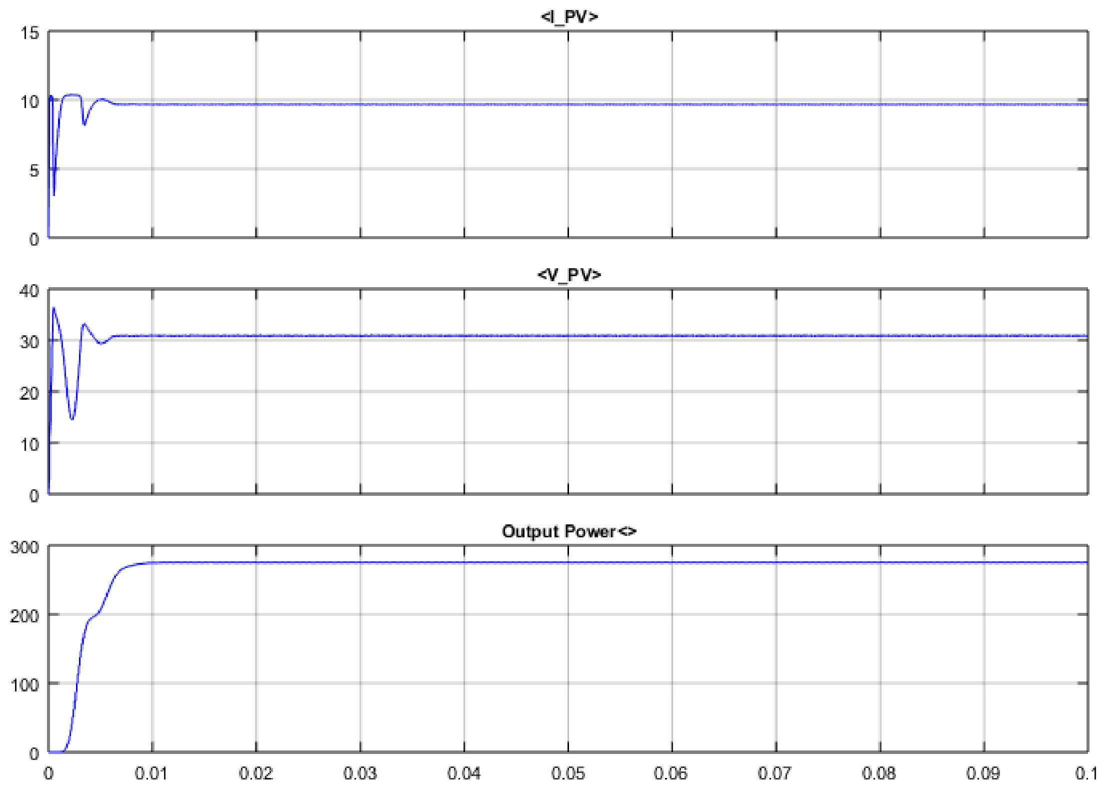


Fig. 6.6 Case 3 Simulated Parameters wrt Time

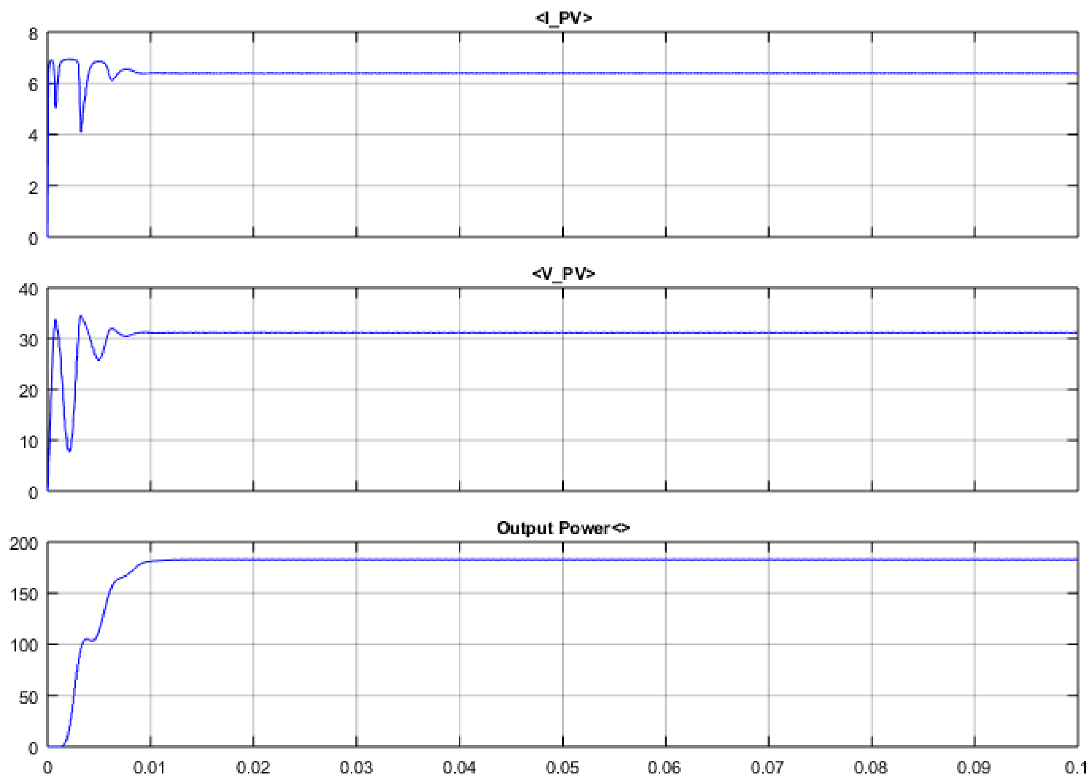


Fig. 6.7 Case 4 Simulated Parameters wrt Time

The following table shows the mean parameters of the simulated system running at MPP.

Case	Irradiation (W/m^2)	Temperature (˚C)	I_{PV} (A)	V_{PV} (V)	P_{out} (W)	Efficiency $= \frac{P_{out}}{P_{MPP}} * 100$
1	1000	15	8.054	32.23	239.2	92.11093991
2	1000	45	8.096	28.22	209.29	91.4729021
3	1200	25	9.658	30.87	275.14	92.20509383
4	800	25	6.394	31.18	182.64	91.36568284

Table 6.9 System parameters at duty cycle obtained from CSA

Conclusions

This project work covered the applications of two metaheuristic algorithms- Crow Search Algorithm & Artificial Bee Colony in electrical systems. The scope of the algorithm was explored in problems of fault location on a single phase transmission line, signal estimation and maximum power point tracking in PV systems. Fault location was estimated for varying conditions like fault resistance, angle of inception of fault and location of the fault on the line. The calculated length showed errors less than 4%. The algorithm shows promising nature for signal estimation as the errors were less than 1%. For maximum power point tracking using a dc-dc cuk converter, efficiencies of the order of 90-92% were obtained and the maximum power point was successfully tracked for different ambient conditions of temperature and irradiation.

Future Scope

This project can be further extended to track maximum power point in real time and for dynamically changing ambient conditions. The performance of metaheuristic algorithms can be studied in such conditions as to determine its adaptability to maintain a steady output with few perturbations as is found in some of the traditional MPPT methods like Perturb & Observe, etc. The performance of metaheuristic algorithms can be compared to these traditional methods. In this project single end method was used for fault estimation, the performance of these algorithms should further be researched for multi-end and wide area methods for fault location in grids.

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