Development of New Metaheuristic Techniques for Parameter Extraction of Solar PV Cell/Module

A thesis submitted to the
University of Petroleum & Energy Studies

For the Award of

DOCTOR OF PHILOSOPHY
IN
ELECTRICAL ENGINEERING

By

ABHISHEK SHARMA

SEPTEMBER 2021

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SEPTEMBER 2021

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DECLARATION CERTIFICATE

I declare that the thesis entitled "**Development of New Metaheuristic Techniques for Parameter Extraction of Solar PV Cell/Module**" has been prepared by me under the guidance of Dr. Abhinav Sharma (Guide), Dr. Rupendra Pachauri (Co-Guide), Assistant Professor, Department of Electrical & Electronics Engineering, University of Petroleum & Energy Studies, Dehradun & Dr. Averbukh Moshe (External Co-guide), Professor, Department of Electrical Engineering and Electronics, Ariel University. No part of this thesis has formed the basis for the award of any degree or fellowship previously.

ABHISHEK SHARMA

RESEARCH & DEVELOPMENT DEPARTMENT

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DATE:

CERTIFICATE

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This is to certify that the thesis titled "**Development of New Metaheuristic Techniques for Parameter Extraction of Solar PV Cell/Module**" submitted by Abhishek Sharma (SAP ID: 500078621) in Partial completion of the requirements for the award of the Degree of Doctor of Philosophy (Engineering) is carried out by him under our joint supervision and guidance.

It is certified that this thesis has not been submitted anywhere else for the award of any other diploma or degree of this or any other University.

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ABSTRACT

The key priority of research community and renewable industries is on increasing the power output of solar PV systems in order to make the generated electricity more cost effective and affordable. The process of estimating the parameters of a solar cell plays a key role in manufacturing and simulating the solar PV system due to non-linear behavior of output characteristics. Various methods come under the category of metaheuristic, iterative and analytic, have been proposed for parameter extraction of solar cell. However, there is requirement of new metaheuristic methods for reducing the error between experimental and simulated values.

A conclusion is drawn from the literature survey that analytical methods used for parameter estimation of solar cell are derived from experimental relation between output voltage and current. But experimental results clearly illustrate that analytical methods are having good ability under standard temperature condition (25° C and 1000 W/m^2) as compared to changing weather conditions. Furthermore, these methods extract only three parameters: shunt resistance, diode ideality factor and parallel resistance without considering any boundary limits.

In the case of analytical methods, the mathematical equations used for parameter estimation are quite tough and very transcendent in nature. There is also requirement of some initial parameters and these parameters are not available in the datasheet provided by manufacturer. Furthermore, in some instances simplifying assumptions are essential which leads to low accuracy of estimated parameters and there is no guaranteed convergence at optimum value.

In the present work six different optimization algorithms are used to adjudge their suitability in getting the appropriate results. The algorithms are GWO, GSA, PSOGSA, SCA, CSO, and CA algorithms. It is found that GWO algorithm take minimum iteration to reach a feasible solution. The comparative results comprehensively demonstrate that GWO outperforms the existing optimization algorithms in terms of root mean square error (RMSE) and the rate of convergence. Furthermore, the statistical results validate and indicate that GWO algorithm is better than other algorithms in terms of average accuracy and robustness. An extensive comparison of electrical performance parameters: maximum current, voltage, power, and fill factor (FF) has been carried out for both PV model.

Tunicate swarm algorithm (TSA) is employed to estimate the optimized value of the unknown parameters of a PV cell/module under standard temperature conditions. The simulation results have been compared with four different, pre-existing optimization algorithms: gravitational search algorithm (GSA), a hybrid of particle swarm optimization and gravitational search algorithm (PSOGSA), sine cosine (SCA), and whale optimization (WOA). The comparison of results broadly demonstrates that the TSA algorithm outperforms the existing optimization algorithms in terms of root mean square error (RMSE) and convergence rate. Furthermore, the statistical results confirm that the TSA algorithm is a better algorithm in terms of average robustness and precision. The Friedman ranking test is also carried out to demonstrate the competency and reliability of the implemented approach.

A hybrid version of whale optimization and particle swarm optimization algorithm is also employed to optimize the photovoltaic cell parameters. The exploitation ability of particle swarm optimization with adaptive weight function is implemented in the pipeline mode with a whale optimization algorithm to improve its exploitation capability and convergence speed. The performance of the proposed hybrid algorithm is compared with six different optimization algorithms in terms of root mean square error and rate of convergence. The simulation result shows that the proposed hybrid algorithm produces not only optimized parameters at different irradiation levels (i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2). The best values of root mean square error generated by the proposed algorithm are 7.1700E-04 and 9.8412E-04 for single-diode and double-diode models.

Furthermore, another novel opposition-based tunicate swarm algorithm is anticipated for parameter estimation of PV module. The proposed algorithm is developed based on the exploration and exploitation components of the tunicate swarm algorithm. The opposition-based learning mechanism is employed to improve the diversification of the search space to provide a precise solution. The parameters of three types of photovoltaic modules (two polycrystalline and one monocrystalline) are estimated using the proposed algorithm. The estimated parameters show good agreement with the measured data for three modules at different irradiance levels. Performance of the developed opposition-based tunicate swarm algorithm is compared with other predefined algorithms in terms of robustness, statistical, and convergence analysis. The root mean square error values are minimum (6.83E-04, 2.06E-04, and 4.48E-06) compared to the tunicate swarm algorithm and other predefined algorithms. Proposed algorithm decreases the function cost by 30.11%, 97.65%, and 99.80% for the SS2018 module, SolarexMSX-60 module, and Leibold solar module, respectively, as compared to the basic tunicate swarm algorithm.

Plan of the Thesis

The scientific community and renewable industries are focusing their efforts on enhancing output of solar PV systems in order to make the generated electricity more cost effective and affordable. Because of the non-linear behavior of output characteristics, the process of estimating the parameters of a solar cell is critical in manufacturing and simulating the solar PV system. For solar cell parameter extraction, several methods, including metaheuristic, iterative, and analytic approaches, have been suggested. However, new metaheuristic methods for reducing the error between experimental and simulated values are required. The entire work reported in the thesis is divided in different chapters. There are six chapters in the thesis. The details of each of these chapters are as follows.

Chapter one contains the basic *Introduction of the problem* taken into consideration in present investigation. Brief idea of various metaheuristic techniques is given in this chapter. How the metaheuristic techniques can be implemented for the optimization of parameters of solar cells/modules is briefly discussed this chapter. Earlier work done in this direction is also revived to give firm basis to the problem. The objectives of the thesis are also mentioned at the end of this chapter.

Chapter two is devoted to the *Review of Various Metaheuristic Algorithms* developed earlier to solve various issues related to parameter optimization of solar cells. The pertinency and weaknesses of these algorithms are revealed. It is determined that each algorithm is established on the foundation of numerous natural activities of diverse living entities. Looking at the harshness of the problems, these algorithms are improved. A comparative analysis of applicability and consequences of these algorithms are provided in this chapter. It is reported that all the algorithms are not suitable for each problem, instead for each problem different algorithms have to be developed.

Chapter three contains the details of implementation of GWO algorithm for the parameter estimation of single-diode and double-diode model for solar cell (RTC France) at standard temperature condition. The comparison of implemented GWO algorithm is carried out with PS, SA, HS, PSO, GA. Furthermore, a comparison in terms of error in voltage, current and power is also performed for the validation of GWO algorithm.

Chapter four describes the implementation of TSA algorithm or parameter estimation of PWP201 PV module at STC (standard temperature conditions). It should be noted that TSA is first time implemented for the problem of parameter estimation of solar panels. In addition to this the effectiveness and accuracy of TSA is compared with GSA, WOA, SCA and PSOGSA. TSA proves its competency in terms of RMSE (taken as objective function).

Chapter five represents the implementation of newly developed hybrid version of PSO and WOA i.e., WOAPSO algorithm for the parameter estimation of solar cell (at STC) and SS2018P PV module (under different levels of irradiance i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2. In proposed WOAPSO algorithm the exploitation ability of PSO is implemented in pipeline mode when WOA stops to improve the best-found solution. The collaboration of both metaheuristic algorithms is able to establish an effective balance between exploitation and exploration search ability.

Chapter Six is devoted to the implementation of a newly anticipated OTSA algorithm for the parameter estimation of single-diode model of two different kinds: polycrystalline and monocrystalline PV panels. Three objective functions: RMSE, MAE and SAE are considered for the optimization. In OTSA, author has combined the opposition-based learning mechanism for initialization of search agents. The integration of OBL does not influence the basic functionality of TSA, and the precision of the optimal solution is enhanced. In this manner, OTSA can limit the number of the initial population, which improves the convergence to the optimal solution since it's exploring the solution space for an optimization problem.

Chapter Seven is devoted to the *Conclusion* of overall results outcome and future scope of regarding the parameter estimation of PV module is also discussed.

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I am very much grateful to God Almighty for without his graces and blessings this study would have not been possible. His mercy was with me throughout my student life and ever more in this study. I thank him for giving me the strength and patience to work through all these years so that today I can stand proudly with my head held high.

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(Abhishek Sharma)

CONTENT TABLE

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LIST OF SYMBOLS & ABBREVIATION

Name of symbols/Abbreviation	Symbols /Abbreviation
Photovoltaic	PV
Single diode model	SDM
Double diode model	DDM
Triple diode model	TDM
Current-voltage	I-V
Power-voltage	P-V
Open circuit voltage	V_{oc}
Photocurrent	I_p
Diode saturation current	I_{sd}
Series resistance	R_s
Shunt resistance	R_{sh}
Ideality factor	a
Standard test conditions	STC
Maximum power point	MPP
Artificial neural network	ANN
Particle swarm algorithm	PSO
Convergence particle swarm optimization	GCPSO
Simulated Annealing Algorithm	SA
Levenberg-Marquardt	LM
Particle swarm algorithm simulated annealing	PSOSA
Root mean square error	RMSE
Artificial Bee Colony Algorithm	ABC
Genetic algorithm	GA
Whale Optimization Algorithm	WOA
Flower Pollination Algorithm	FPA
Bee pollinator Flower Pollination Algorithm	BPFPA
Biogeography-based Optimization	BBO

Direct Current	**DC**
Cat Swarm Optimization	**CSO**
Bat Algorithm	**BA**
Bat Hybrid Cuckoo Search	**BHCS**
Cuckoo search optimization	**CS**
Grey Wolf Optimization	**GWO**
Parallel Particle Swarm Optimization	**PPSO**
Improved Whale Optimization Algorithm	**IWOA**
Leavy Distributed Bat Algorithm	**LDBA**
Grey Wolf Optimization Cuckoo search optimization	**GWO-CS**
Cuckoo Search Biography Based Optimization	**CS-BBO**
Harmony Search	**HS**
Gravitational Search Algorithm	**GSA**
Short Circuit Current	I_{sc}
Current at Maximum Power Point	I_{mpp}
Irradiance	W/m^2
Temperature	$^{\circ}C$
Differential Evolution	**DE**
Pattern Search	**PS**
Harmony Search	**HS**
Bacterial Foraging Optimization	**BFO**
Artificial Bee Swarm Optimization	**ABSO**
Improved Teaching Learning-Based Optimization	**ITLBO**
Non-Sorting Genetic Algorithm	**NSGA**
Shunt Resistance Current	I_{sh}
Load Current	I_l
Cell Output Voltage	V_l
Temperature	**T**
Boltzmann Constant	k_b

Vector	**X**
Number of Experimental Data	**k**
Alpha	**α**
Beta	**β**
Delta	**δ**
Omega	**ω**
Constant	$\vec{A}$
Random Number	R_1
Random Number	R_2
Sine Cosine Algorithm	**SCA**
Individual Absolute Error	**IAE**
Relative Error	**RE**
Maximum Current	I_m
Maximum Voltage	V_m
Maximum Power	P_m
Change in Maximum Current	ΔI_m
Change in Maximum Power	ΔP_m
Fill Factor	**FF**
Tunicate Swarm Algorithm	**TSA**
Number of cells in series	N_s
Number of cells in parallel	N_p
Gravity Force	$\vec{G}$
Whale Optimization and Particle Swarm Optimization	**WOAPSO**
Measured Value of Power	$P_{measured}$
Simulated Value of Power	$P_{simulted}$
Watt	**W**
Current	**A**
Gradient Based Optimizer	**GBO**
Harris-Hawk Optimizer	**HHO**

Heap-based Optimizer	**HBO**
Slime Mould Algorithm	**SMA**
Chaotic Whale Optimization Algorithm	**CWOA**
Levy Flight Trajectory-based Whale Optimization Algorithm	**LWOA**
Binary Whale Optimization Algorithm	**BWOA**
Hybrid Approach Grey Wolf Optimization	**HAGWO**
Colliding Bodies Optimization Whale Optimization Algorithm	**CBO-WOA**
Memetic Whale Optimization Algorithm	**MWOA**
Moth Flame Whale Optimization Algorithm	**MFOWOA**
Sine-Cosine Whale Optimization Algorithm	**SC-WOA**
Pattern Search Whale Optimization Algorithm	**PS-WOA**
Brain Storm Whale Optimization Algorithm	**BS-WOA**
Constriction Factor	c_1, c_2
Inertia Weight	**w**
Current Iteration	**t**
Resistance	**Ω**
Central Processing unit	**CPU**
High Quality	**HQ**
Giga Hertz	**Gz**
Giga Byte	**GB**
Random Access Memory	**RAM**
Standard Deviation	**SD**
Multiple learning backtracking search algorithm	**MLBSA**
Enhanced Harris Hawk optimization	**EHHO**
Improved Jaya algorithm	**IJAYA**
Generalized Opposition Based Teaching Learning Based Optimization	**GOTLBO**
Minimum	**Min**

Maximum	**Max**
Second	**s**
Chaos Particle Swarm Optimization	**CPSO**
Improved Adaptive Differential Evolution	**IADE**
Biogeography Based Optimization Algorithm with Mutation Strategies	**BBO-M**
Nelder-Mead Modified Particle Swarm Optimization	**NM-MPSO**
Opposition-Based Learning	**OBL**
Opposition-Based Tunicate Swarm Algorithm	**OTSA**
Summation of Absolute Error	**SAE**
Mean Absolute Error	**MAE**
Measured Value of Current	$I_{measured}$
Calculated Value of Current	$I_{calculated}$
No-Free-Lunch	**NFL**
Ant Lion Optimization	**ALO**

CHAPTER -1

INTRODUCTION

Nowadays, growth in artificial intelligence with embedded system application has led to a new era in computing, impacting almost all science and engineering fields. Specifically, soft computing methods, as a part of artificial intelligence aimed at creating more stable and human-behaving systems, have proved to be excellent options to deal with challenging problems that arise in a wide range of energy applications. Soft-computing methods implemented to energy-related problems regularly face data-driven tasks such as problems of optimization, classification, clustering, or prediction. In several instances, these problems are closely related to alternative technologies such as renewable energy capacity assessment, energy efficiency systems design, or very specific smart grid energy system applications.

Accelerated ignition of fossil fuel sources for energy production may lead to major environmental problems such as greenhouse gas formation in the surrounding air, acid rain, ozone layer exhaustion, and global climate change [1-3]. Solar photovoltaic (PV) energy has depicted excellent promise as a substitute for fossil fuel sources in many countries around the world, particularly in the area of decentralised electric power generation.

Theoretical modelling and computer computation of PV systems are required to comprehend the output characteristics, effectiveness, and performance, as well as to analyse the system in response to changes in solar irradiance and temperature [4]. Many existing literatures have explained the single diode (SD), double diode (DD), and triple diode (TD) corresponding circuit models in order to recognise the non-linear current-voltage (I-V) and power-voltage (P-V) features of the PV system. Because of its easiness and reliability, the single diode model (SDM) is the most frequently used PV model. However, at smaller irradiance levels and temperatures, the SDM's reliability is closely related to the open circuit voltage (V_{oc}) [5]. The variables of the generated photocurrent (I_p) connected in parallel to the diode, saturation current flow through the diode (I_{sd}), series resistance (R_s), shunt resistance (R_{sh}), and ideality factor (a) are all depicted in this system. The inclusion of an additional diode to the SDM is recognised as the Double Diode Model (DDM), which can enhance the reliability of the PV system by accounting for recombination current damage at the depletion zone. The DDM is denoted by seven parameters, which are as follows: reverse saturation currents of two diodes (I_{sd1} and I_{sd2}), diode ideality factors: diffusion (a_1) and recombination (a_2), I_p, R_s, and R_{sh}. Addition of a third diode to the DDM is known as TDM. Third diode is employed to demonstrate the vital non-ideality of solar cells that cause leakage current to start happening at the grain border and surface of solar cells. Accurate prediction of PV parameters using the equivalent model of solar cell/module is needed to visualise the behaviour and analyse the effectiveness of the PV system under both standard test conditions (STC) and real measured conditions with temperature and irradiation variations. Predicting PV parameters can lead to incorrect power converter sizing decisions as well as controller instability [6].

The modelling parameters of any PV panel could be taken from the data sheet provided by the manufacturers under STC. Conventional methods are classified in two parts as an analytical and numerical method for the evaluation of solar cell parameters. Analytical methods require several key points of I-V curve information such as open voltage circuit (V_{oc}), short-circuit current (I_{sc}), maximum power point (MPP) voltage and current values are necessary including I-V curve axial intersection paths [7]. The reliability of this method relies largely on the selected I-V curve points, which may lead to significant errors when selecting these points incorrectly. The exactness of this procedure is based on the value of the initial parameters, cost and fitting algorithms extracted. The limits of the traditional extraction method are the failure of the ability to give precise results when model parameters are increased. The numerical and analytical methods are discussed in detail in the references [8-10]. The artificial neural network (ANN) is one of analytical method that can be employed only for temperature and in insulation measurements to estimate the photovoltaic parameters. However, when environmental conditions such as shading occur, the reliability of this method degrades [11]. Most of the optimization problems have unfortunately been described as NP-hard issues that cannot be resolved in the polynomial time zone unless the NP is equal to P. Thus, with exact mathematical methods, only small-scale cases can be handled. Heuristics and metaheuristics could be categorised rather than renouncing the researchers' idea of using possible working methods (approximate methods) which can find a sufficiently good solution in a reasonable time. The major difference between the two is that heuristics depend more on the problem than metaheuristics. Recent research indicates that a more accurate and reliable approach for the prediction of PV parameters would be provided by the metaheuristics algorithm [12]. The disadvantages of using analytical and numerical methods can be overcome by utilising EA's stochasticity, which predicts optimal PV parameter values by significantly minimising the predefined objective function. The complete process of parameter estimation for solar cell is depicted in Figure 1.1.

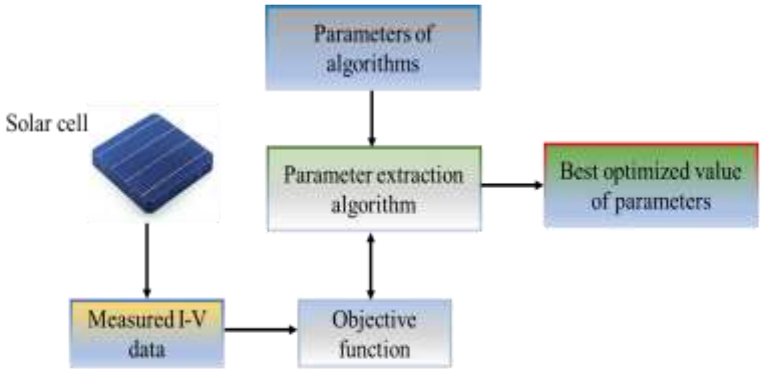

Figure 1.1. Process flow diagram of parameter estimation of solar cell

1.1 *Research objectives*

1) To estimate the parameters of solar PV cell/module under constant irradiance and temperature by using metaheuristic-based algorithms.
2) To develop a new robust metaheuristic algorithm (modified/hybrid).
3) To estimate the parameters of solar PV cell/module under different climatic condition by using new developed metaheuristic algorithm (modified/hybrid).

1.2.Plan of the Thesis

The scientific community and renewable industries are focusing their efforts on enhancing output of solar PV systems in order to make the generated electricity more cost effective and affordable. Because of the non-linear behavior of output characteristics, the process of estimating the parameters of a solar cell is critical in manufacturing and simulating the solar PV system. For solar cell parameter extraction, several methods, including metaheuristic, iterative, and analytic approaches, have been suggested. However, new metaheuristic methods for reducing the error between experimental and simulated values are required. The entire work reported in the thesis is divided in different chapters. There are seven chapters in the thesis. The details of each of these chapters are as follows.

Chapter one contains the basic *Introduction of the problem* taken into consideration in present investigation. Earlier work done in the field of parameter estimation of solar cell is revived to give firm basis to the problem. The objectives of the thesis are also mentioned at the end of this chapter.

Chapter two is devoted to the *Review of Various Metaheuristic Algorithms* developed earlier to solve various issues related to parameter optimization of solar cells. The pertinency and weaknesses of these algorithms are revealed. It is determined that each algorithm is established on the foundation of numerous natural activities of diverse living entities. Looking at the harshness of the problems, these algorithms are improved. A comparative analysis of applicability and consequences of these algorithms are provided in this chapter. It is reported that all the algorithms are not suitable for each problem, instead for each problem different algorithms have to be developed.

Chapter three contains the details of implementation of GWO algorithm for the parameter estimation of SDM and DDM for solar cell (RTC France) at standard temperature condition. The comparison of implemented GWO algorithm is carried out with PS, SA, HS, PSO, GA. Furthermore, a comparison in terms of error in voltage, current and power is also performed for the validation of GWO algorithm.

Chapter four describes the implementation of TSA algorithm for parameter estimation of PWP201 PV module at STC (standard temperature conditions). It should be noted that TSA is first time implemented for the problem of parameter estimation of solar panels. In addition to this the effectiveness and accuracy of

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Chapter five represents the implementation of newly developed hybrid version of PSO and WOA i.e., WOAPSO algorithm for the parameter estimation of solar cell (at STC) and SS2018P PV module (under different levels of irradiance i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2. In proposed WOAPSO algorithm the exploitation ability of PSO is implemented in pipeline mode when WOA stops to improve the best-found solution. The collaboration of both metaheuristic algorithms is able to establish an effective balance between exploitation and exploration search ability.

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Chapter Seven is devoted to the *Conclusion* of overall results outcome and future scope of metaheuristics algorithms for parameter estimation of solar cell/module.

CHAPTER-2

LITERATURE REVIEW

The utilization of renewable energy sources is expanding rapidly, and solar energy applications focused on PV systems are becoming increasingly popular. Effective parameter identification is important for reliable PV cell modeling and assessment of PV system characteristics due to the nonlinear nature of output I-V and P-V curves. Because of the rapid development of computer technology and swarm intelligence techniques, numerous successful meta-heuristic algorithms were introduced to improve this phenomenon further. In this section a comprehensive review of metaheuristic algorithms with their modifications is provided and evaluated quantitively in terms of accuracy, robustness, and efficiency. The population-based metaheuristic algorithms are of three types: evolutionary based, swarm based, and other algorithms as shown in Figure 2.1.

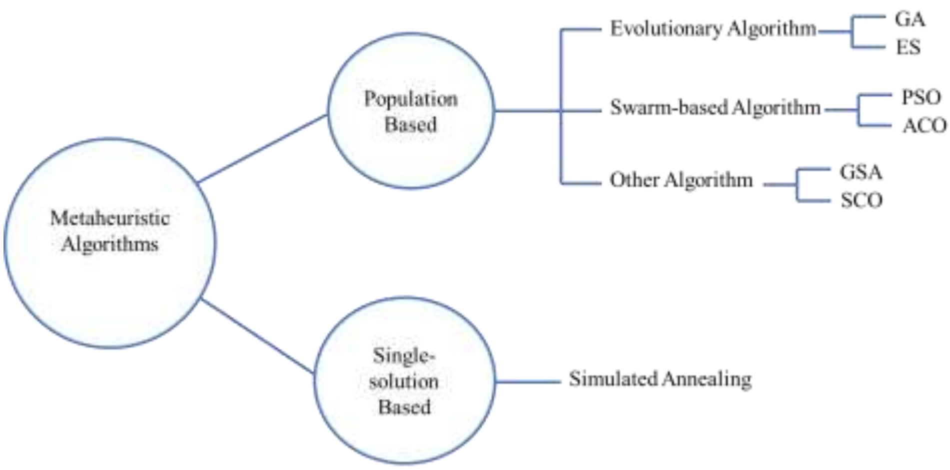


Figure 2.1. Characterization of Metaheuristic Algorithms

2.1 Particle Swarm Optimization (PSO)

PSO algorithm is basically originated from the searching behavior of group of birds and is proposed by kennedy [13], where each particle updates its personal best position according to the global best position of entire swarm. It is having good ability to solve the optimization problems. However, distinct enhancements are being recommended to lessen the convergence time for complex optimization problems. In [14], authors have proposed a novel guaranteed convergence particle swarm optimization (GCPSO) to extract the parameters of solar PV module by utilizing the single diode model (SDM) and double diode Model (DDM). The efficiency of CGPSO is compared with other algorithms existing in the literature and simulation results indicate that it is effective in avoid the premature convergence for both complex and multimodal optimization problems. In velocity update equation a scale factor is in-cooperated to update the position of global best particle. In another study [15], a parallel PSO is implemented to overcome the problem of computational cost and complexity related to the objective function used for parameter extraction of solar PV cell.

2.2 Simulated Annealing Algorithm (SA)

Simulated annealing algorithm imitates the behavior of gradual cooling process of metal [16] and often used for the optimization problems having discrete and large search space, proposed by van & aarts. In this algorithm the position of searching agent is updated on the basis of random walk and very promising in finding the global optimum value of solution. However, due to inability of producing guaranteed optimal solution and slow convergence rate authors have anticipated a hybrid method in [17], where Levenberg-Marquardt (LM) method is combined with SA for extracting the parameters of solar PV cell. A damping factor is introduced for updating the position of search agents for increasing convergence rate. Later on, a new variant hybrid PSOSA is introduced by Mughal *et al.* [18] to prevent the premature convergence. In this method the global best solution generated by the PSO is further evaluated by the SA at each iteration. The efficiency of hybrid PSOSA is compared with five other metaheuristics algorithms. The statistical analysis clearly depicts the effectiveness of hybrid PSOSA in terms of low value of RMSE.

2.3 Artificial Bee Colony Algorithm (ABC)

Artificial bee colony algorithm is inspired by the foraging behavior of the honeybees for the search of food (nectar) for the bee's colony. It is a swarm based and metaheuristics algorithm developed by Karaboga, in 2005, for optimizing the NP hard problems [19]. Two basic concepts: self-organization and partition of labor, are necessary and useful to achieve swarm intelligent behavior. Tuba and Bacanin [20] proposed a hybrid version of basic ABC algorithm by implementing the local search characteristics of fire fly algorithm to improve the exploitation process. The anticipated hybrid algorithm was evaluated on twenty unimodal and multi-modal standard benchmark test functions. A comparative analysis was also carried out in terms of robustness and efficiency with the pre-existing population-based algorithms: tabu search, PSO, GA and simulated annealing (SA). To improve solar energy system performance, accurate modelling of solar cells ' current vs. voltage (I–V) characteristics has attracted the attention of various research. The main drawback of comprehensive modelling is the lack of information on the exact parameter values representing the solar cell. Since such parameters cannot be obtained from datasheet specifications, an optimization technique is required to adapt experimental data for accurate electrical modeling of the solar cell. ABC algorithm is found to be more promising method for the extraction of solar cell's parameter over pre-existing algorithms in the literature [21].

2.4 Whale Optimization Algorithm (WOA)

Whale optimization algorithm mimics the hunting behavior of special types of humpback whales and is recently anticipated by Mirjalili [22] in the year of 2016. Where, the whales use spiral of bubble-net attacking procedure to chase the prey with the help of best search agent existing in the swarm. In order to extract the solar cell parameters, a chaotic WOA is anticipated by the authors in [23]. Where, a chaotic system is integrated. Chaotic system is defined as a non-linear dynamic and deterministic system having the characteristics such as randomness and possess sensitivity towards primary defined conditions. These characteristics make it suitable for providing the diversity in the population of WOA to increase the searching ability and to evade the problem of getting trapped in local optimum. Later on, an investigation carried out by the authors in [24]. Where, an improved variant of basic WOA is introduced for effective parameter extraction of solar PV module under standard temperature condition i.e., 25° C and 1000 W/m^2. In this investigation, the drawback of premature convergence due to existence of aggravate exploitation in basic version of WOA is removed by introducing two prey strategy. The simulation results clearly depict that two-prey strategy for hunting the prey provides a good tradeoff between exploration and exploitation.

2.5 Flower Pollination Algorithm (FPA)

Flower pollination algorithm imitates the process of flower pollination occurring in the plants and proposed by Xin-She Yang [25] in the year of 2012. This algorithm utilizes the biotic and abiotic process that are being used in flower pollination. Where, biotic process represents the exploration stage while abiotic process denotes the exploitation stage. A probability-based switching rule is employed to provide balance between exploitation and exploration process. Authors in [26] proposed a method for parameter extraction of solar cell by implementing the FPA. Where the data for estimating the parameter is driven from three sources: literature survey, experimental and datasheet of solar panel. A new and easy to implement hybridization method known as bee pollinator FPA is evolved by the researchers in [27] where the adaption process of bee's indulged in discarding the worst pollination and results in increment of randomness ability of basic FPA to avert the local optimum. Simulation results indicate the effectiveness of BPPFA in terms of low RMSE for both SDM and DDM under different climatic conditions (i.e., varying temperature and irradiance level). Furthermore, statistical analysis is carried out to validate the superiority of BPPFA in terms of standard deviation.

2.6 Biogeography-based Optimization (BBO)

Biogeography-based optimization algorithm is proposed by Simon. It relies on the concept of island biogeography and utilizes a mathematical model to illustrate how the species from one island migrates, how the some species on island become extinct, how the species arise from one island to other island [28]. In this algorithm, there are only two main operators: mutation and migration. In order to remove the defects such as poor exploitation, not selecting good solution in every iteration and unawareness of fitness value of solution, authors in [29] suggested a mutation strategy based BBO for the DC parameter estimation of solar cell. The simulation results show the superiority of BBO-M over other existing algorithms in literature survey. The experimental readings are taken by using RTC France solar cell under standard temperature condition.

2.7 Cat Swarm Optimization (CSO)

Cat swarm optimization (CSO) algorithm is derived by monitoring the behaviour of cat and consists of two modes: seeking mode and target mode [30] and is proposed by chu *et al.*. In this algorithm, search agents use the seeking mode to identify the best solution according to the fitness value and change their position rapidly towards the best solution. The exploitation of the solution in a defined search space is accomplished by seeking mode while the exploration of the solution is achieved by tracing mode. In a recent study [31] authors have implemented the CSO for parameter estimation of solar PV cell. Simulation results evidently show that the I-V curve drawn on the basis of estimated value given by CSO fits better with the I-V curve obtained experimentally. The sensitivity analysis of algorithm is also carried out by the authors and results depict that the best performance of CSO can be achieved by using one dimension and small step mutation approach. Furthermore, the statistical analysis demonstrates the ability of CSO in generating the global optimum solution and effective execution in terms of good convergence speed.

2.8 Bat Algorithm (BA)

Bat algorithm mimics the echolocation features of bat for finding the prey and recently proposed by Xin-She yang [32] in the year of 2010. In this algorithm during the hunting of prey the pulse rate of ultrasonic wave is high at low amplitude. When the location of prey is determined then pulse rate becomes low and amplitude becomes high. This process defines the exploration and exploitation behavior of search agents. Deotti & Pereira [33] anticipated an enhance variant of basic bat algorithm by introducing levy flight approach for better exploitation. In addition to this a dynamic adjustment approach is also introduced to avoid the solutions that are exceeding the search boundaries. Authors have estimated the DC parameter of solar PV module by using only SDM. The reliability of anticipated algorithm is analyzed statistically in terms of mean, mode, median and standard deviation. Levy flight-based bat algorithm outperforms the other pre-existing algorithms such as GA, PSO and BHCS.

2.9 Cuckoo search optimization (CS)

Cuckoo search optimization algorithm is proposed by yang & Deb. In nature distinct species of birds, insects and fish are brood parasites, i.e., these species rely on others to grow their own infants. The CS algorithm [34] is inspired by this natural breeding parasite phenomenon, in which cuckoo birds lay their eggs in the nest of host birds. The algorithm is also inspired from the random walk behavior of animals and birds, widely known as levy flight. In this the step-length is calculated according to the heavy tailed probability distribution. A hybrid GWO and CSA was proposed for parameter extraction of different solar PV modules under different operating conditions [35]. In another study [36], authors have suggested a new variant of CS by hybridizing it with BBO for solving the complex non-linear parameter estimation problem of solar cell. This hybridization provides a good balance between exploration and exploitation search ability as compared with basic CS.

2.10 Grey Wolf Optimization (GWO)

Grey wolf optimization algorithm relies on hunting behavior of grey wolf and is anticipated recently by Mirjalili *et al.* [37] in the year of 2014. Where wolfs in a group follows a social hierarchy for encircling and hunting the prey. The GWO possess various advantages over the other existing optimization algorithms. It is an easy computational algorithm with reduced burden of computation. The application flexibility for parameter extraction problem without any deep change in existing structure, makes it more usable. The problem of convergence and local optima was also avoided. The most interesting aspect with respect to applicability of this optimization technique is that concept can easily be transformed into programming language for the real time implementation. Nayak *et al*. [38] implemented GWO algorithm for DC parameter estimation of solar PV module by utilizing SDM and DDM. However, they have extracted only three parameters and compared it with only PSO and thus doesn’t confirm the applicability of GWO and requires further investigation on the basis of statistical analysis. Analysis of metaheuristic algorithms adapted for parameter estimation of PV cells / modules is summarized in Table 2.1.

Table 2.1. Analysis of meta-heuristic algorithms adapted for parameter estimation of PV cells / modules.

References/ Year	Algorithms	Used data	SDM	DDM	PV cell/Module
[14], 2018	GCPSO	Experimental data	✓	✓	SM55 PV cell
[15], 2018	PPSO	Experimental data with I-V curves	✓	✓	TITAN-12–50 panel
[17], 2014	SA	I-V data from the manufacturer	✓	✓	KC200GT PV module
[18], 2017	PSOSA	Synthetic and experimental I-V data	✓	✓	57 mm diameter R.T.C. France solar cell
[21], 2014	ABC	Experimental data	✓	X	KC200GT PV module
[23], 2017	WOA	Real measured I-V dataset	✓	✓	57 mm diameter R.T.C. France solar cell
[24], 2018	IWOA	Experimental data	✓	✓	KC200GT PV module

[26], 2015	FPA	Experimental data	✓	✓	SM55 PV cell
[29], 2014	BBO	Real measured I-V dataset	✓	✓	57 mm diameter R.T.C. France solar cell
[31], 2016	CSO	Synthetic I-V data	✓	✓	KC200GT PV module
[33], 2019	LDBA	Experimental data	✓	X	57 mm diameter R.T.C. France solar cell
[35], 2020	GWO-CS	Experimental data	✓	✓	SM55 PV cell
[36], 2019	CS-BBO	Synthetic I-V data	✓	✓	KC200GT PV module
[38], 2019	GWO	Synthetic I-V data	✓	X	57 mm diameter R.T.C. France solar cell

2.11 Scope of Novel Research Work

A comprehensive literature survey has been carried out on related aspects of parameter estimation of solar cell/PV module to identify the research gaps are summarized in Table 2.2 as follows.

Table 2.2. Some prominent issues left in previous research papers.

References/Year	Approaches/ Conclusion	Scope of work
[38], 2019	• GWO algorithm for DC parameter estimation of solar PV module by utilizing SDM and DDM. • RMSE is taken as objective function. • Extracted only three parameters: R_s, R_{sh} and a.	• In this research work, all the five parameters: I_{ph}, I_0, R_s, R_{sh} and a can be extracted. • An extensive comparison can be done with other metaheuristic techniques such as GA, ABC, HS, CS. • Simulations by considering different level of irradiance and temperature can be considered to show the robustness of GWO.
[39], 2019	• Salp swarm-based optimization algorithm is anticipated to extract the solar cell parameters. • To validate the accuracy of the algorithm two parameters: absolute error and mean square error are used.	• Authors have extracted the parameters under two irradiance level 366 and 810 W/m^2. A wider range can be considered to show the effectiveness of the algorithm. • Only DDM is considered in this study. TDM can be considered for further validation. • A hybridization with other existing

		metaheuristics can also be considered to increase the convergence speed.
[40], 2018	• Moth flame algorithm is anticipated by the authors and TDM is used for modeling the complicated behaviour of I-V curve. • Two parameters absolute error and mean bias error are considered as benchmark for the validation of proposed methodology.	• An enhancement is required for increasing the convergence speed and reducing the computational time. • For effectiveness of algorithm a wide range of temperature and irradiance can be considered.
[24], 2018	• An enhance variant of basic WOA is anticipated for parameter estimation to conquer the pre mature convergence problem. • Sum of individual absolute error is considered as a benchmark parameter for the evaluation of optimized value of parameters.	• Authors have considered only standard temperature conditions. • There is no study presented on the basis of electrical performance such as fill factor and output efficiency.
[41], 2017	• Bacterial foraging algorithm is implemented to extract the five	• Sum of individual errors and Root mean square of error can be

	parameters of solar PV module under different climatic conditions. • Only three parameters: R_s, R_{sh} and a are extracted under different level of irradiance and temperature.	considered as an objective function for further validation of robustness of algorithm. • Authors have considered on SDM. A DDM can also be acknowledged for further evaluation.
[42], 2017	• An adaptive based modification is done in PSO for the parameter extraction. • RMSE is taken as an objective function to minimize the error between experimental and simulated values of output current and voltage.	• Authors have considered only standard temperature conditions. • SDM is used for modeling the solar cell. DDM can also be considered. • There is no study presented on the basis of electrical performance such as fill factor and output efficiency.
[43], 2017	• Genetic algorithm is employed for parameter extraction under standard temperature condition. • SDM is used for the study.	• A hybridized variant of GA with other metaheuristic algorithms can be designed for effective parameter extraction. • DDM and TDM can also be studied under varying irradiance and temperature.
[44], 2016	• Analytical method is	• An extensive study can be

	employed for optimized parameter identification of solar cell by using SDM and DDM. • Authors have considered a wide range of irradiance and temperature level for validating the effectiveness of employed method.	done by implementing the metaheuristic-based algorithms for further validation. • Experimental values of current and voltage can be measured for mono-crystalline and thin file solar PV module.
[45], 2016	• GSA algorithm is used for parameter extraction of solar PV module and compared with GA at different level of irradiance varying from 200 to 1000 W/m^2. • Sum of individual errors is taken as objective function for the estimating the optimized parameters.	• An extensive comparison can be done with other metaheuristic techniques such as bat algorithm, honeybee, pattern search. • Root mean square of error can be also considered as an objective function for estimating the optimized parameters.
[31], 2016	• Cat swarm optimization algorithm is anticipated to extract the solar cell parameters	• Changing climatic conditions can also be considered for further validation of effectiveness

	by using SDM and DDM. • Mean relative error and mean absolute error is studied as benchmark for measuring the performance of algorithm.	of implemented algorithm. • A hybridization with other existing metaheuristics can also be considered to reduce the computational time.

2.12 Motivation for Research Work

- The process of estimating the parameters of a solar cell plays a key role in manufacturing and simulating the solar PV system due to non-linear behavior of output characteristics.
- There is requirement of new metaheuristic methods for reducing the error between experimental and simulated values.
- A conclusion is drawn from the literature survey that analytical methods used for parameter estimation of solar cell are derived from experimental relation between output voltage and current.
- Furthermore, these methods extract only three parameters: shunt resistance, diode ideality factor and parallel resistance without considering any boundary limits.

CHAPTER-3

IMPLEMENTATION OF GWO ALGORITHM FOR PARAMETER ESTIMATION OF SOLAR CELL/MODULE

3.1 Introduction

The depletion of fossil fuel resources and resulting environmental impact due to their usages embarks the need of alternate energy resources [46]. Solar energy is one of the most promising alternate source for the fossil fuel. The free to access energy of sunlight can be well extracted by means of solar photo voltaic panels. The rapid adoption of solar energy by domestic and industrial sector makes it a vital source to be explored [47]. Enormous researches have been performed and is being carried out for the betterment of the power output from the PV panels [3, 48] . Despite of the very low operational and maintenance cost, it has various limitation associated with it. The major limitation in execution and implementation of the solar PV power plants is very high capital cost for installation [49] . Taking into consideration the operational limitations and non-linear nature of characteristics of solar PV modules [50]. This non-linearity makes it difficult for any probability and approximation to increase the efficiency. Every PV panel is designed to operate at maximum efficiency, as defined by the manufacturer, only if the practical operational parameters are somewhat close to or coinciding with MPP [51-53]. The dynamic behavior, due to the non-linearity of I-V characteristics of solar cells makes it essential to determine the MPP through simulation techniques for better operational efficiency [54]. The parameters provided by the PV panel manufacturer don't specifies the model parameters. The given information states the open circuit voltage (V_{oc}), short circuit current (I_{sc}) and current at maximum power point (I_{mpp}) under standard test conditions (i.e., 1000 W/m^2, 25°C). The practical parameters vary at every instant with change in weather condition and the ageing effect of PV also alters the parameters [3, 55, 56].

The core unit of PV system is solar cell, and it is of utmost priority to extract the parameters for a close analysis of the PV panels performance around its MPP. The simulation study of cells combined all together give the performance analysis of entire PV panels [55, 57] . The equivalent circuit for single and double diode model for parameter extraction is the recent and most widely used approach. The method of parameter extraction can be bifurcated in two major categories: analytical and optimization methods [58-61]. Although the analytical methods are the simplest and yields result quickly, but it misses the accuracy under normal day conditions with variable lighting. The deterministic ways of parameter extraction such as Newton- Raphson, non-linear least square, Lambert W-functions [62], iterative curve fitting [63], conductivity method [64], Levenberg-Marquardt algorithm [65] are having many boundaries such as continuity, differentiability and convexity related to objective functions. The boundary conditions further impose limitations on the usage of the above analytical methods, as they obtain local minima when dealing with multi-modal problems. Thus, analytical methods are not suitable enough to extract the parameters.

To get more accurate and precise parameters from nonlinear implicit equations with high accuracy, evolutionary algorithms [66] were proposed. The bio related algorithms are more accurate and powerful optimization algorithms to simplify nonlinear transcendental equations as it doesn't include complex mathematics. Some of the recent optimization algorithms used for the parameter extraction are GA [67], differential evolution(DE) [7], simulated annealing(SA) [68] , pattern search (PS) [69] , harmony search (HS) [70] , CS [71], flower pollination algorithm [26], bacterial foraging optimization (BFO) [41], bird mating [72], artificial bee swarm optimization (ABSO) [73], chicken swarm optimization (CSO) [74] and PSO [75]. The proposed algorithms suffer with the problem of premature convergence. The primary disadvantage of GA is that it involves wide parameter optimization search space which makes the system quite complicated and slow. The problem of large search space was overcome by implementing PSO. However, it imposed the problem of randomly chosen initial parameter value. The value exchange in SA between the cooling timetable and the original temperature makes it less popular. There is a likelihood that PS will choose an incorrect pattern, leading to premature convergence or no convergence. PSO with reverse barrier restriction for R_s, R_{sh}, and *a* is suggested for fast and coherent convergence of optimization issue to global optima, considering the temperature impact to reduce the modelling errors in DE [76]. Although the BFO technique offers excellent outcomes but involving too many parameters has complicated the scheme and imposed a computational strain. Authors in [77], implemented improved teaching learning based optimization (ITLBO) , where a good trade-off is established between exploration and exploitation by eliminating the worse learner. This increases the global search ability of the population in defined search space. A hybridization approach is carried out by the researchers in [78] for parameter extraction of solar PV cell. In this approach hybridization of two algorithms: firefly and PS are implemented. The exploration phase is completed by the firefly algorithm during first half iteration and then PS algorithm takes control of population for the exploitation phase. A new OBL approach is incorporated with whale optimization and shuffled complex evolutionary algorithm for optimization of solar cell parameters [79, 80]. This approach is tested on unimodal as well as on multimodal benchmark functions and simulation results clearly shows the robustness of the algorithms.

The GWO possess various advantages over the other existing optimization algorithms. It is an easy computational algorithm with reduced burden of computation. The application flexibility for parameter extraction problem without any deep change in existing structure, makes it more usable. The problem of convergence and local optima was also avoided. The most interesting aspect with respect to applicability of this optimization technique is that concept can easily be transformed into programming language for the real time implementation. Tsai *et al.* [81] implemented GWO algorithm for path planning of mobile robot in static environment. Multi-objective function was used for smoothness of path and obstacle avoidance. Simulation results depicted that anticipated approach was able to generate the optimal path from starting position to target position with obstacle avoidance. Authors in [82] have proposed a separate multi-objective GWO to improve the real-world scheduling case from a welding cycle. The experiment and the statistical analysis depicted the superiority of the GWO over the non-sorting genetic algorithm

(NSGA-II) and the Pareto evolutionary algorithm. In the field of Bioinformatics, Jayapriya and Arock [83] used a parallel model of GWO for problem alignment of multiple sequences. This method proved the effectiveness of anticipated algorithm in terms of time-complexity. In this chapter GWO algorithm is employed to estimate the optimized value of parameters for PV cells. In order to validate the performance and precision of the GWO technique, the results are compared with well know pre-existing algorithms in the literature. This chapter presents five parameter extractions for SD and seven parameters extraction for DD equivalent circuit of solar PV cell.

The organization of chapter is as follows: the problem formulation and mathematical model for solar PV cell is presented in section 3.2. In section 3.3 a brief introduction of GWO algorithm is discussed and its implementation to estimate the optimized value of unknown parameters of SDM and DDM. In section 3.4 simulation results of GWO algorithm are discussed and compared with pre-existing metaheuristic algorithm. Finally, section 3.5 gives a conclusive remark to summarize the chapter.

3.2 Problem Formulation

In this section, the equivalent circuits of a PV cell are formulated using SDM and DDM. These equivalent circuit models are used to describe the current-voltage characteristics of a solar cell.

3.2.1 Single-diode model for PV cell

The equivalent circuit of SDM is depicted in Figure 3.1. The relation between current and voltage at output terminal is expressed as follows [84, 85]:

$$I_l = I_p - I_d - I_{sh} \tag{3.1}$$

where I_l stands for cell current in output, I_p represents the photogenerated current, I_d stands for diode current, I_{sh} represents the current flowing through parallel resistance.

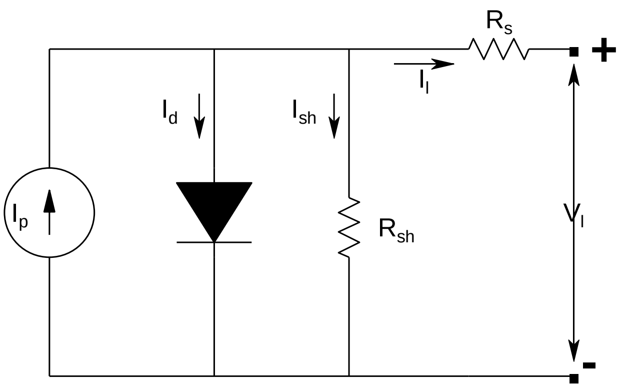


Figure 3.1. Equivalent circuit of SDM for PV cell

As per Shockley equation, the diode current is expressed as:

$$I_d = I_{SD}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_1k_BT}\right)-1\right] \tag{3.2}$$

where, I_{SD}, V_l, a_1, R_s, k_B, T and q are reverse saturation current, cell output voltage, diode ideality constant, series resistance, the Boltzmann constant (1.3806503×1023 J/K), junction temperature (ºK) and the electron charge (1.60217646×10-19 C), respectively. The current flowing through shunt resistance can be described as follows:

$$I_{sh} = \frac{V_l+I_lR_s}{R_{sh}} \tag{3.3}$$

where, R_{sh} stands for shunt resistance.

By merging eq. (3.1) -(3.3), we arrive at:

$$I_l = I_p - I_{SD}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_1k_BT}\right)-1\right]-\frac{V_l+I_lR_s}{R_{sh}} \tag{3.4}$$

In above equation, five model parameters (I_p, I_{SD}, a_1, R_s and R_{sh}) are needed to be optimized using measured I-V data of the solar cell. The SDM is considered good and easy to regenerate the I-V curve. However, this model lacks the phenomena of the recombination effect in the diode, that is why it is not the most suitable model.

3.2.2 Double diode model for PV cell

Figure 3.2 depicts the DDM for PV cell. The DDM is considered precise and complicated than that of SDM. The relation between current and voltage at output terminal for the DDM is expressed as [84, 85]:

$$I_l = I_p - I_{d1} - I_{d2} - I_{sh}$$

$$= I_p - I_{SD1}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_1k_BT}\right) - 1\right] - I_{SD2}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_2k_BT}\right) - 1\right] - \frac{V_l+I_lR_s}{R_{sh}}$$

(3.5)

where, I_{SD1} and I_{SD2} represent the diffusion and saturation current respectively. I_{d1} and I_{d2} represents the first and second diode current. Eqn. (5) defines seven unknow model parameters: I_p, I_{SD1}, I_{SD2}, a_1, a_2, R_s and R_{sh},which are required to be optimized using experimental data of current and voltage for the solar cell.

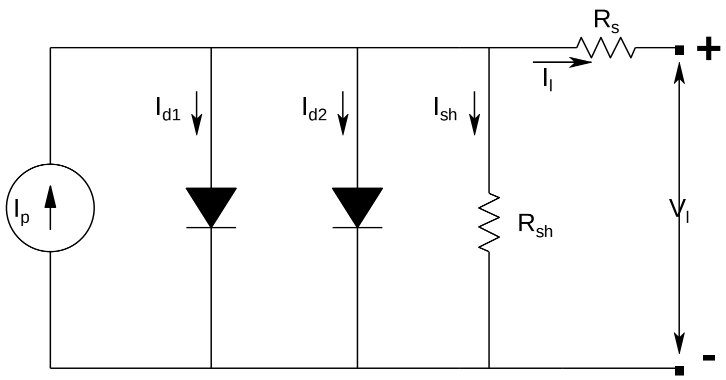


Figure 3.2. Equivalent circuit of DDM for PV cell

3.2.3 Objective Function

The key purpose of this work is to optimize the unknown parameters for both the models (SDM and DDM) and to reduce the error between experimental and estimated data. The objective function for error is formulated as:

$$RMSE = \sqrt{\frac{1}{k}\sum_{N=1}^{k} f(V_l, I_l, \mathrm{X})^2} \quad (3.6)$$

where, V_l and I_l are the measured voltage and current of PV module. The parameter ‘k’ stands for the number of experimental data set. The best solution found by GWO is represented by a vector X.

For the SDM,

$$\begin{cases} f_{single}(V_l, I_l, X) = \; I_p - I_{SD}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_1k_BT}\right) - 1\right] - \frac{V_l+I_lR_s}{R_{sh}} - I_l \\ \qquad\qquad (X = \; I_p, I_{SD}, a_1, R_s, R_{sh} \;) \end{cases} \tag{3.7}$$

For the DDm,

$$\begin{cases} f_{double}(V_l, I_l, X) = \; I_p - I_{SD1}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_1k_BT}\right) - 1\right] \\ \quad -I_{SD2}\left[exp\left(\frac{q(V_l+I_lR_s)}{a_2k_BT}\right) - 1\right] - \frac{V_l+I_lR_s}{R_{sh}} - I_l \\ \qquad (X = \; I_p, I_{SD1}, I_{SD2}, a_1, a_2, R_s, R_{sh} \;) \end{cases} \tag{3.8}$$

3.2.4 GWO Based Optimization

Grey wolf optimization proposed by Mirjalili *et.al.* [37] is a swarm intelligence technique which is originated from grey wolves. The behavior of hunting and social hierarchy of grey wolves is mathematically defined in terms of an algorithm to solve high dimensional optimization problems. The leadership hierarchy of grey wolves are simulated by four types i.e., alpha (α), beta (β), delta (δ) and omega (ω). These categories of grey wolves live on an average in a group of five to ten and present an important behavior of group hunting. Mainly the hunting process is accomplished by α, β, δ while ω tracks these three wolves.

The three main stages of GWO are tracking, encircling, and hunting the prey which are depicted in Figure 3.3 and mathematically modeled as follows:

Step 1. Initiate the random population of grey wolves within defined search space:

$$P_i = \left(p_i^1 \ldots\ldots\ldots p_i^j \ldots\ldots. p_i^j\right) for \; i = 1, 2, \ldots\ldots\ldots., n \tag{3.9}$$

where, p_i^d represents the location of ith particle in the jth dimension and *n* signifies the dimension of search space.

Step 2. Calculate fitness of all search agents, if the problem is the minimization problem, the fittest (minimum) value of the fitness function is considered as X_α, second and third minimum values are considered as X_β, X_δ respectively. The rest value of fitness functions is considered as X_ω.

Step 3. There is an update in terms of the location of each search agents, in each iteration, according to the best search agents ($X_\alpha, X_\beta, X_\delta$) using equations (3.10) and (3.11):

$$\vec{D}_\alpha = \left|\vec{C}_1 * \vec{X}_\alpha - \vec{X}\right|, \quad \vec{D}_\beta = \left|\vec{C}_2 * \vec{X}_\beta - \vec{X}\right|, \qquad \vec{D}_\delta = \left|\vec{C}_3 * \vec{X}_\delta - \vec{X}\right| \quad (3.10)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 * (\vec{D}_\alpha), \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 * (\vec{D}_\beta), \quad \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 * (\vec{D}_\delta) \quad (3.11)$$

$$\vec{X}(k+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (3.12)$$

where, k signifies the current iteration, $\vec{A}_1$, $\vec{A}_2$, $\vec{A}_3$ and $\vec{C}_1$, $\vec{C}_2$, $\vec{C}_3$ are the coefficient vectors of alpha, beta and delta, and $\vec{X}$ denotes the location vector of grey wolf. The generalized expression of coefficient vectors $\vec{A}$ and $\vec{C}$ are defined as:

$$\vec{A} = 2 * \vec{a} * \vec{r}_1 - \vec{a} \quad (3.13)$$

$$\vec{C} = 2 * \vec{r}_2 \quad (3.14)$$

where, the component $\vec{a}$ is linearly reduced from 2 to 0 over the course of iterations and r_1, r_2 are the random vectors in the range [0,1].

Step 4. Update the coefficient vectors $\vec{A}$ and $\vec{C}$ in each iteration.

Step 5. Calculates the fitness of each search agent and update $X_\alpha, X_\beta, X_\delta$ in each iteration.

Step 6. Jump to step 3 until the termination criteria is met. The algorithm stops at two conditions either at maximum number of iterations or the least error criteria is met.

Step 7. In the last iteration the returned value of $\vec{X}_\alpha$ represents the global minimum and the positions corresponding to it represents the solution of the problem.

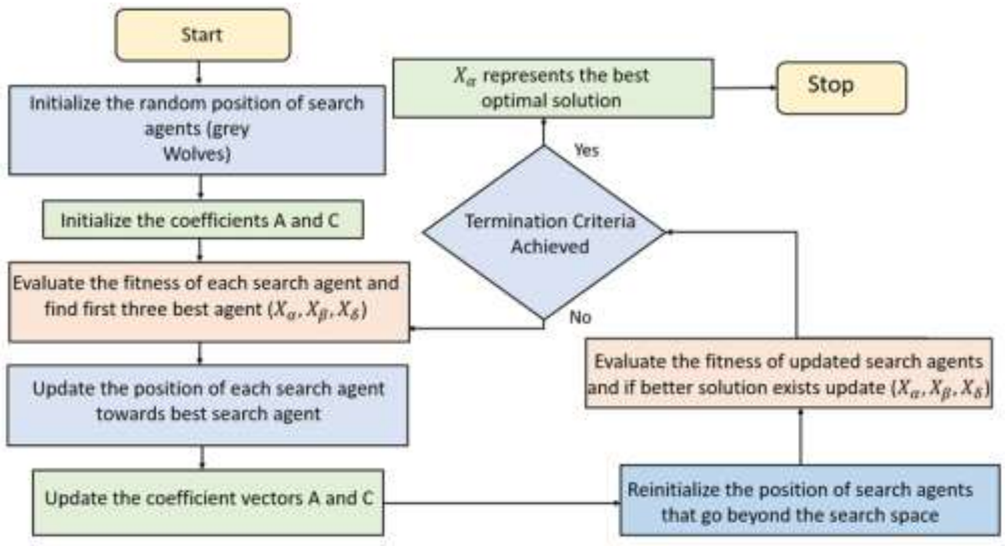


Figure 3.3. Flowchart of GWO algorithm

3.3 Implementation of GWO For Parameter Extraction

3.3.1 Single-Diode Model

Step 1. Initialize the population of search agents of fifth order dimension in the search space. The fifth order dimension represents the photovoltaic current (I_p), series resistance (R_s), shunt resistance (R_{sh}), diode saturation current (I_{SD}) and diode ideality factor (a_1). The range of these parameters are [0-1, 0.001-0.5, 0-100, 0.01-0.5, 1-2].

Step 2. Regulate the fitness of all agents in the search space using eq. (3.7).

Step 3. Update the position of the agents at every iteration using GWO. The algorithm is designed to work in the minimization mode thus the location of particles that acquire minimum cost represents the optimized parameters of SDM with minimum RMSE.

3.3.2. Double-Diode Model

Step 1. Initialize population of search agents of seventh order dimension in the search space. The seventh order dimension represents the photovoltaic current (I_p), series resistance (R_s), shunt resistance (R_{sh}), diode saturation currents (I_{SD}, I_{SD1}) and diode ideality factor (a_1, a_2). The range of these parameters are [0-1, 0.001-0.5, 0-100, 0.01-0.5, 0.01-0.5, 1-2, 1-2].

Step 2. Regulate the fitness of all agents in the search space using eq. (3.8).

Step 3. Update the position of all agents at every iteration using GWO. The algorithm is designed to work in the minimization mode thus the location of particles having minimum cost represents the parameters of DDM with minimum RMSE.

3.4 Results and Discussion

In this section, to check efficiency, the GWO optimization technique is implemented to optimize the two parameter extraction problems efficiently and derived from literature. These problems consider mainly two distinct cases: SDM and DDM for a solar PV cell. The experimental observations of current and voltage for both considered case is taken from [86] where the dataset is measured from a 57mm diameter industrial silicon solar cell with model name of R.T.C. France under STC (i.e. 1000 w/m^2 and 33°C). The measured data set consists of total 26 samples of voltage and current. For fair comparison the search ranges (i.e. upper and lower bound) for each individual parameter is tabulated in Table 3.1, that are same as already used by the researchers in [23, 69, 85, 87].

To validate the effective performance in terms of convergence rate, robustness and quality of result, GWO is compared with five pre-existing and well established algorithms in the literature, they are PS [69], SA [88], HS [70], PSO [89] and GA [90]. To perform the experiment, size of population and maximum number of objective function evaluations are kept at 30 and 50,000 respectively. To avoid the contingency total number of 30 independent runs are carried out. For testing and programming the algorithm, MATALB 2018 software is used to perform all the statistical test. Details of hardware and software is tabulated in Table 3.2.

Table 3.1. Range of parameters for SDM and DDM

Parameter	**SDM**		**DDM**	
	Lower Bound	**Upper Bound**	**Lower Bound**	**Upper Bound**
Ip(A)	0	1	0	1
Isd(μA)	0.01	0.5	0.01	0.5
Rs(Ω)	1E-03	0.5	1E-03	0.5
Rsh(Ω)	0	100	0	100

a_1	1	2	1	2
I_{sd1}(μA)			0.01	0.5
a_2			1	2

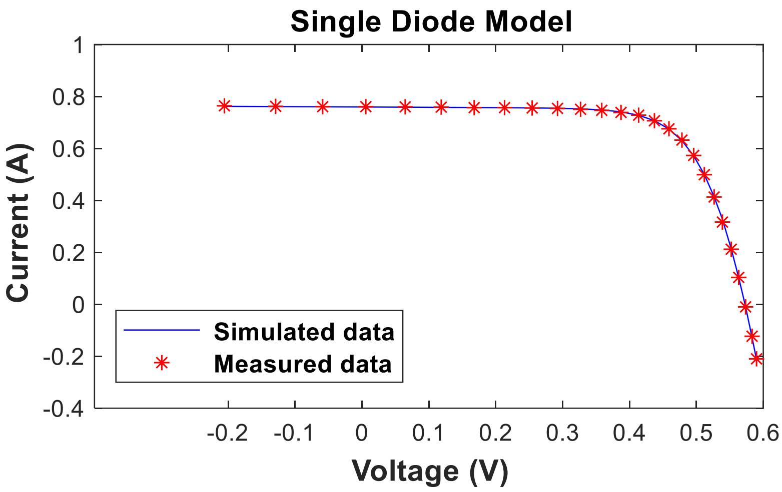
Table 3.2. The Specification of hardware used in simulating the system

Name	Setting
Hardware	
CPU	Intel Core i7
Frequency	3.6 Giga Hertz
RAM	8 Giga Byte
Hard Drive	2 Tera Byte
Software	
Operating System	Windows 10
Language	MATLAB 2018a

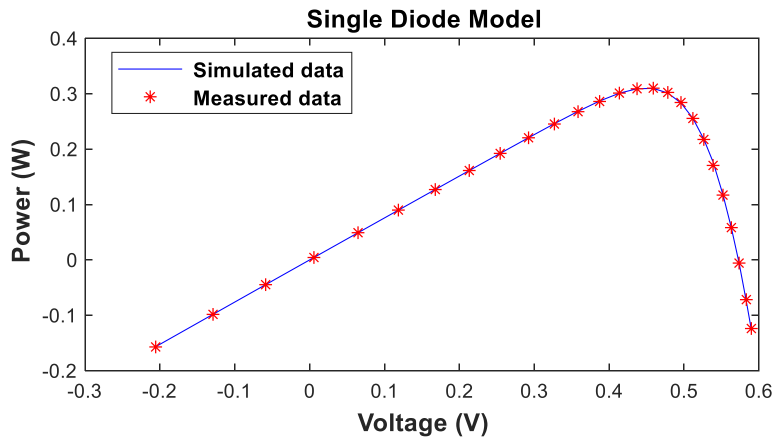
3.4.1 Simulation Results For SDM

There are only five parameters (I_p, I_{sd}, a_1, R_s, R_{sh}) which are required to be optimized in the case of SDM. Table 3.3 represents the values of parameters optimized by GWO and RMSE, for the comparison. It can be clearly analyzed that GWO produces the least RMSE of 9.4094E-04 which is very low as compared with the results of other five algorithms: GSA, PSOGSA, SCA, CSO and CA. Here RMSE values are acquired as the index for the evaluation of results with previously existing algorithms implemented by the researchers.

The characteristics curve of current-voltage and power voltage for SDM is redrawn based on best optimized parameters obtained by implementing the GWO algorithm and clearly depicted in Figure 3.4. It is depicted in Figure 3.4, that calculated data obtained by the GWO is very effectively in coincidence with the experimental data set, under STC (i.e., 1000 w/m^2 and 33°C), all over the voltage range. Table 3.4 represents the individual absolute error (IAE) in between calculated and experimental data set. Every determined value of IAE in Table 3.4 is less than 5.4244E-03 which indicates that the parameters optimized by the GWO are very precise. The distribution of values for all optimized parameters is shown with the help of box plot in Figure 3.5. Boxplot is a systematic way to represent the distribution of the data based on five parameters median, first quartile (Q1) minimum, second quartile (Q2) and maximum. The boxplot of I_{ph} parameter, the second quartile (Q2) shows that 75% of data is 0.7597 A. In the case of R_s parameter, the second quartile (Q2) shows that 75% of data is 0.0342 Ω, similarly for R_{sh} the second quartile (Q2) shows that 75% of data is equal to 83.01 Ω. While for I_{sd} parameter the second quartile (Q2) depicts that 75% of data is 0.499 µA. This distribution of optimized parameters clearly shows the effectiveness of GWO algorithm in terms of average accuracy.



(i)



(ii)

Figure 3.4. Experimental and estimated data comparison using GWO for SDM (i) characteristics curve of I-V (ii) characteristics curve of P-V

Table 3.3. Comparison of GWO with other parameter estimation methods for SDM

Algorithms	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE
GSA	0.7575	0.5	0.0396	58.71143	1.5507	1.16E-03
PSOGSA	0.7677	0.01	0.0522	18.45874	1.218	1.26E-02
SCA	0.6493	0.454	0.0235	44.07847	1.5863	2.08E-03
CSO	0.76065	0.41	0.035318	60.01702	1.5279	9.73E-04
CA	0.76017	0.6609	0.0322	80.8217	1.5179	1.45E-03
GWO	0.7597	0.499	0.0342	83.0131	1.5483	9.41E- 04

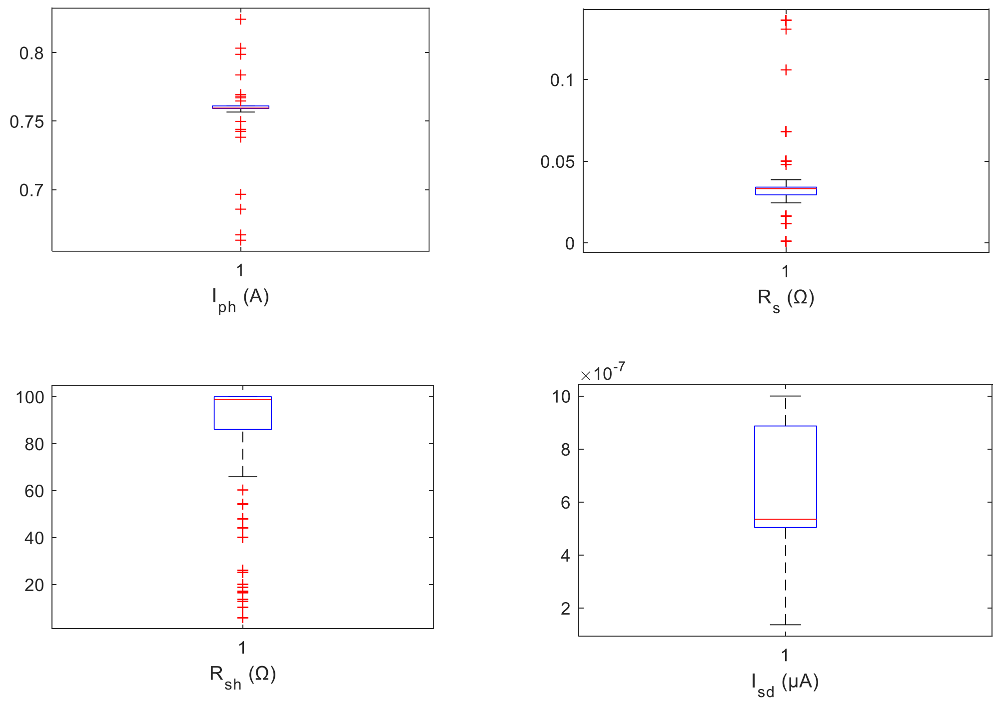


Figure 3.5. Boxplot of single diode parameters (I_{ph}, R_s, R_{sh}, I_{sd}) using GWO algorithm

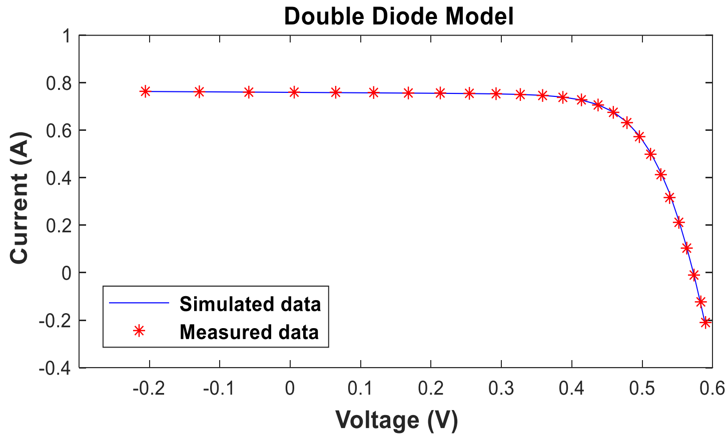
Table 3.4. Value of absolute error and estimated current obtained by GWO for SDM.

Observations	V_l (V)	I_l (A)	I_l estimated (A)	IAE
(I)	0.2057	0.764	0.7619	0.00208
(II)	0.1291	0.762	0.7609	0.0010
(III)	0.0588	0.7605	0.7601	0.0003
(IV)	0.0057	0.7605	0.7593	0.0011
(V)	0.0646	0.76	0.7586	0.0013
(VI)	0.1185	0.759	0.7579	0.0010
(VII)	0.1678	0.757	0.7573	0.0003
(VIII)	0.2132	0.757	0.7566	0.0003
(IX)	0.2545	0.7555	0.7558	0.0003
(X)	0.2924	0.754	0.7545	0.0005
(XI)	0.3269	0.7505	0.7523	0.0018
(XII)	0.3585	0.7465	0.7481	0.0016
(XIII)	0.3873	0.7385	0.7406	0.0021
(XIV)	0.4137	0.728	0.7275	0.0004
(XV)	0.4373	0.7065	0.7066	0.0001
(XVI)	0.459	0.6755	0.6746	0.0008
(XVII)	0.4784	0.632	0.6299	0.0020
(XVIII)	0.496	0.573	0.5712	0.0017
(XIX)	0.5119	0.499	0.4993	0.0003
(XX)	0.5265	0.413	0.4139	0.0009
(XXI)	0.5398	0.3165	0.3279	0.0014
(XXII)	0.5521	0.212	0.2130	0.0010
(XXIII)	0.5633	0.1035	0.1026	0.0008
(XXIV)	0.5736	-0.01	0.0096	0.0003
(XXV)	0.5833	-0.123	0.1284	0.0054
(XXVI)	0.59	-0.21	0.2137	0.0037
Sum of IAE				0.0436

3.4.2 Simulation Results For DDM

In the case of DDM, there are basically seven parameters (I_p, I_{sd}, I_{sd1}, a_1, a_2, R_s, R_{sh}) which are required to be optimized. The values of optimized parameters and minimum of RMSE are presented in Table 3.5, for the comparison. GWO also produces the best value in terms of RMSE (1.24501E-03) as compared to other algorithms. The characteristics curve in terms of current-voltage and power-voltage for DDM is redrawn based on best optimized parameters obtained by implementing the GWO algorithm and clearly depicted in Figure 3.6. The values of individual absolute error are depicted in Table 3.6.

From Figure 3.6, it can be clearly projected that the estimated data based on optimized parameters is in highly coincidence with the experimental data set. From Table 3.6, it can be easily analyzed that all the values of IAE are less than 1.2880E-02, which demonstrates the accuracy of optimized parameters produced by GWO. The distribution of values for all optimized parameters is shown with the help of box plot in Figure 3.7. Boxplot is a systematic way to represent the distribution of the data based on five parameters median, first quartile (Q1) minimum, second quartile (Q2) and maximum. The boxplot of I_{ph} parameter, the second quartile (Q2) shows that 75% of data is 0.7601 A. In the case of R_s parameter, the second quartile (Q2) shows that 75% of data is 0.033 Ω, similarly for R_{sh} the second quartile (Q2) shows that 75% of data is equal to 55.31 Ω. While for I_{sd1} parameter the second quartile (Q2) depicts that 75% of data is 0.4356 µA and for I_{sd2} parameter the second quartile (Q2) depicts that 75% of data is 0.352 µA. This distribution of optimized parameters clearly shows the effectiveness of GWO algorithm in terms of average accuracy.



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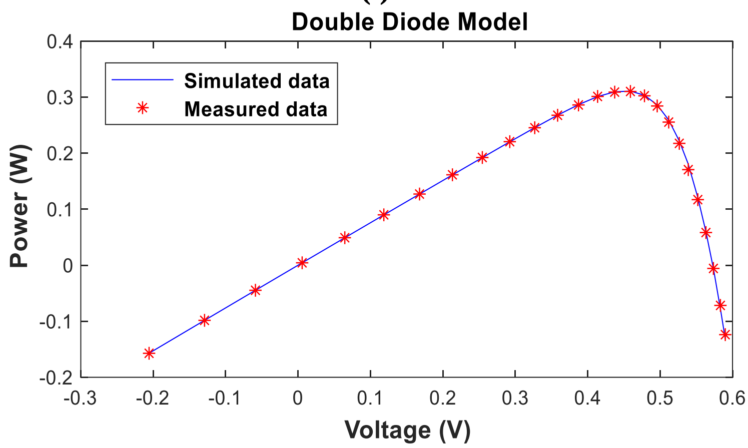


(ii)

Figure 3.6. Experimental and estimated data comparison using GWO for DDM (i) characteristics curve of I-V (ii) characteristics curve of P-V

Table 3.5. Comparison of GWO with other parameter estimation methods for DDM

Algorithms	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	R_s (Ω)	R_{sh} (Ω)	a_1	a_2	RMSE
GSA	0.764	0.05	0.01	0.0345	37.78	1.9943	1.5492	2.03E-02
PSOGSA	0.7611	0.432	0.01	0.0347	61.72	1.999	1.5489	1.48E-01
SCA	0.7622	0.126	0.0125	0.0595	52.4903	2	1.2197	3.18E-02
CSO	0.7676	0.0216	0.0947	0.0335	54.9501	1.4606	1.8363	1.73E-03
CA	0.7583	0.0466	0.001	0.0551	52.567	1.8312	1.3339	3.10E-03
GWO	0.7601	0.4356	0.352	0.0333	55.3129	2	1.512	1.245E-03

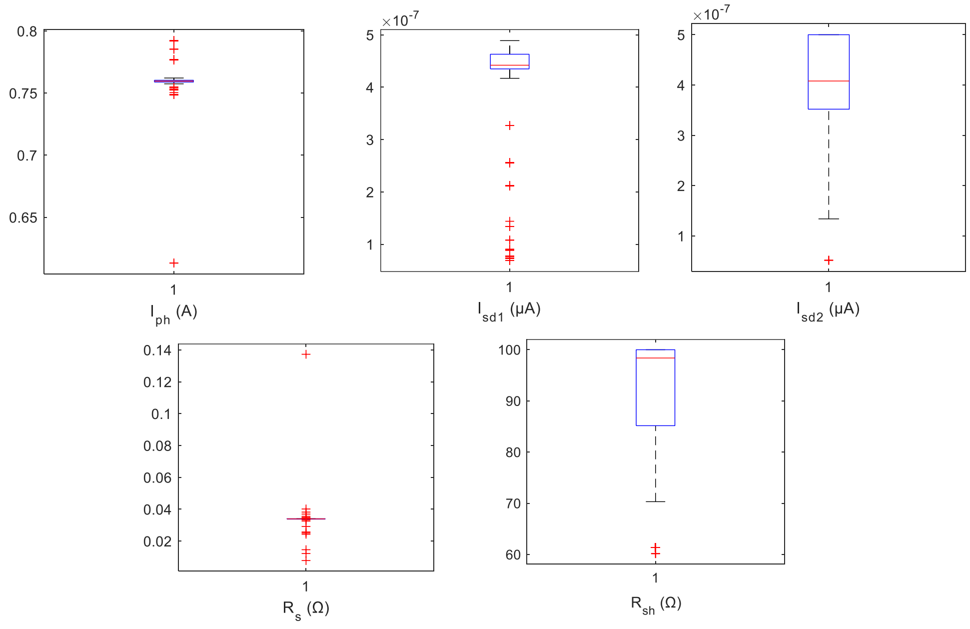


Figure 3.7. Boxplot of double diode parameters (I_{ph}, I_{sd1}, I_{sd2}, Rs, R_{sh}) using GWO algorithm

Table 3.6. Value of absolute error and estimated current obtained by GWO for DDM

Observations	V_l (V)	I_l (A)	I_l estimated (A)	IAE
(I)	0.2057	0.764	0.7633	0.0006
(II)	0.1291	0.762	0.7619	0.00002
(III)	0.0588	0.7605	0.7607	0.0002
(IV)	0.0057	0.7605	0.7595	0.0009
(V)	0.0646	0.76	0.7584	0.0015
(VI)	0.1185	0.759	0.7574	0.0015
(VII)	0.1678	0.757	0.7565	0.0004
(VIII)	0.2132	0.757	0.7556	0.0013
(IX)	0.2545	0.7555	0.7545	0.0009
(X)	0.2924	0.754	0.7531	0.0008
(XI)	0.3269	0.7505	0.7509	0.0004
(XII)	0.3585	0.7465	0.7469	0.0004
(XIII)	0.3873	0.7385	0.7398	0.0013
(XIV)	0.4137	0.728	0.7274	0.0005
(XV)	0.4373	0.7065	0.7076	0.0011
(XVI)	0.459	0.6755	0.6770	0.0015
(XVII)	0.4784	0.632	0.6339	0.0019
(XVIII)	0.496	0.573	0.5768	0.0038
(XIX)	0.5119	0.499	0.5060	0.0070
(XX)	0.5265	0.413	0.4211	0.0081
(XXI)	0.5398	0.3165	0.3347	0.0182
(XXII)	0.5521	0.212	0.2185	0.0065
(XXIII)	0.5633	0.1035	0.1058	0.0023
(XXIV)	0.5736	-0.01	0.0100	0.0001
(XXV)	0.5833	-0.123	0.1334	0.0104
(XXVI)	0.59	-0.21	-0.2228	0.0128
Sum of IAE				0.0854

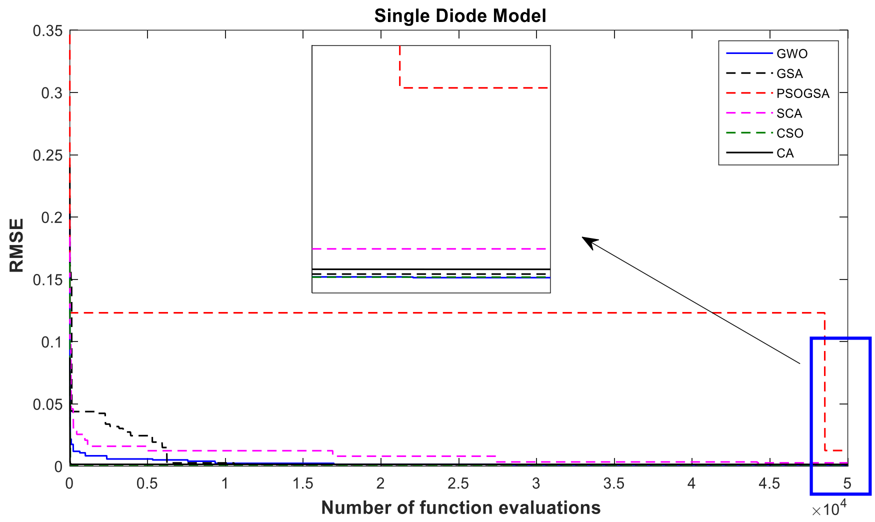
3.4.3 Statistical evaluation with previous implemented algorithms

This section presents statistical evaluation based on mean, minimum, maximum and standard deviation of RMSE for all previous implemented methods, and a comparison with respect to precision and consistency of the distinct algorithms in total of thirty runs and depicted in Table 3.7. The mean of RMSE is calculated to evaluate the precision of algorithms and standard deviation is calculated to evaluate the consistency of the parameter estimation methods.

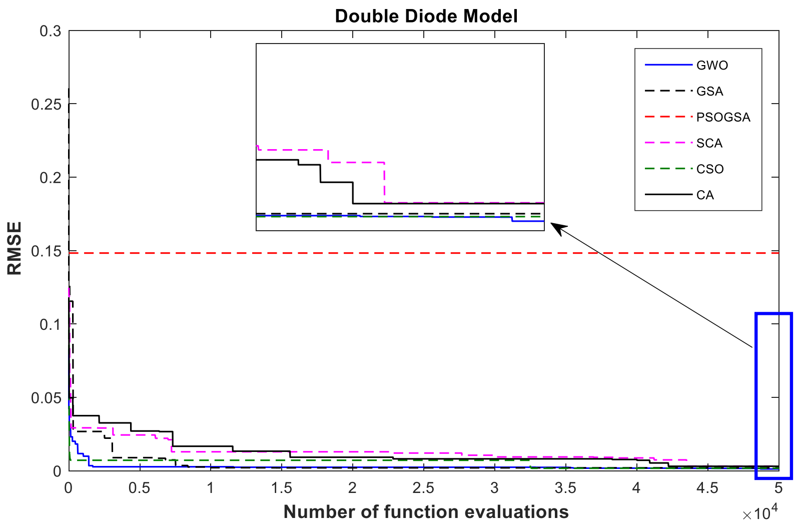
Table 3.7. Statistical evaluation of distinct algorithms implemented in previous investigation for both models

Model	Algorithm	RMSE			
		Minimum	Mean	Maximum	Standard Deviation
SDM	PS	1.494E- 02	-	-	-
	SA	1.90E- 02	-	-	-
	HS	9.95E-04	1.26E- 03	1.417E- 03	1.198E- 04
	PSO	1.39E-03	-	-	-
	GA	1.87E-02	-	-	-
	GWO	9.409E-04	1.044E- 03	1.353E- 03	1.405E- 05
DDM	PS	1.518E- 02	-	-	-
	SA	1.664E- 02	-	-	-
	HS	1.260E- 03	1.07E- 03	1.352E- 03	1.462E- 04
	PSO	1.660E- 02	-	-	-
	GA	3.604E- 01	-	-	-
	GWO	1.245E- 03	1.05E- 03	2.426E- 03	1.095E- 04

From Table 3.7, GWO provides the best result in terms of all four indicators: minimum, standard deviation, maximum and mean as compared to other algorithms. HS attains the second-best value in terms of minimum RMSE followed by PSO, PS, SA and GA respectively. In the case of DDM, GWO provides best value in terms of minimum and standard deviation of RMSE while HS gets best value in terms of mean and maximum and it can be easily predicted that HS is good in terms of reliability as compared to GWO. The convergence curves of GWO for SDM and DDM is presented in Figure 3.8. In the case of SDM, GWO converges to optimal value of estimated parameters at RMSE equivalent to 9.4094E-04 in 48,920 evaluations. For DDM, GWO converges to optimal value of unknown parameters at RMSE of 1.2450E-03 at 49,210 evaluations.



(a)



(b)

Figure 3.8. Convergence curves (a) for different algorithms for SDM (b) for different algorithms for DDM

Based on the above discussed comparisons, it can be determined that the GWO algorithm is very good with respect to reliability and accuracy of solution to estimate the model parameters of distinct types (SDM and DDM) of solar PV models.

3.4.4 Analysis of Electrical Performance

In this subsection the proposed GWO technique is compared with the algorithms PS, SA, HS, PSO and GA based on mainly four electrical performance parameters: maximum current (I_m), voltage (V_m), power (P_m) and fill factor (FF) for the SDM and DDM of PV cell. The error in maximum current and power is represented by ΔI_m and ΔP_m.

Table 3.8.
Performance comparison of electrical parameters

Algorithm	Single Diode Model					Double Diode Model				
	I_m(A)	V_m(V)	P_m(W)	ΔI_m(A)	ΔP_m(W)	I_m(A)	V_m(V)	P_m(W)	ΔI_m(A)	ΔP_m(W)
PSO	65.97	45.9	30.28	4.68	0.73	65.7	45.9	30.16	4.95	0.85
HS	66.02	45.9	30.3	4.63	0.71	65.87	45.9	30.24	4.78	0.77
PS	65.15	45.9	29.9	5.5	1.11	38.8	45.9	16.05	31.85	14.96
SA	65.29	45.9	29.97	5.36	1.04	65.37	45.9	30	5.28	1.01
GA	65.3	45.9	29.97	5.35	1.04	30.67	45.9	26.12	39.98	4.89
GWO	67.46	45.9	30.96	3.19	0.05	67.66	45.9	30.97	2.99	0.04

The estimated values of single diode parameters I_{ph}, I_{SD}, a_1, R_s and R_{sh} are considered to obtain the values of performance parameters (I_m, V_m, P_m) for all the optimization methods. From Table 3.8 and Figure 3.9, it is observed that the best values of I_m, V_m and P_m (in percentage) are obtained by GWO algorithm as 67.46 A, 45.9 V and 30.96 W respectively. The second-best values are obtained by HS while GA gets the lowest values. GWO also gets best value of FF as 68.69% which is 1.46% higher than HS and followed by PSO, GA, SA and PS as shown in Figure 3.10.

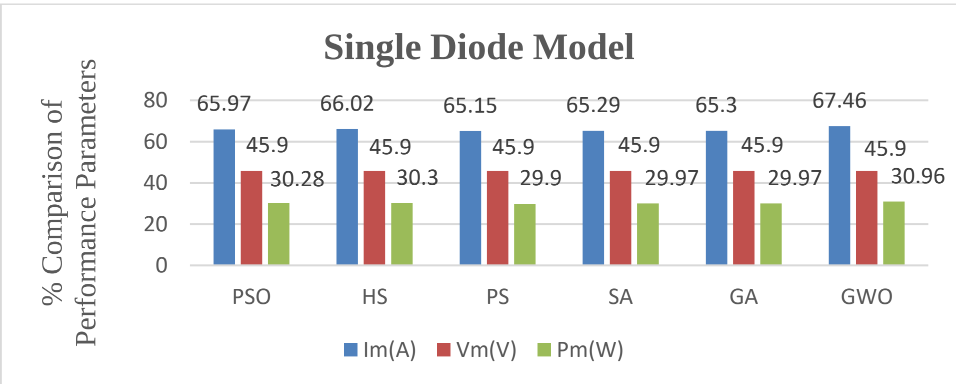


Figure 3.9. Comparison of performance parameters (I_m, V_m, P_m) for SDM

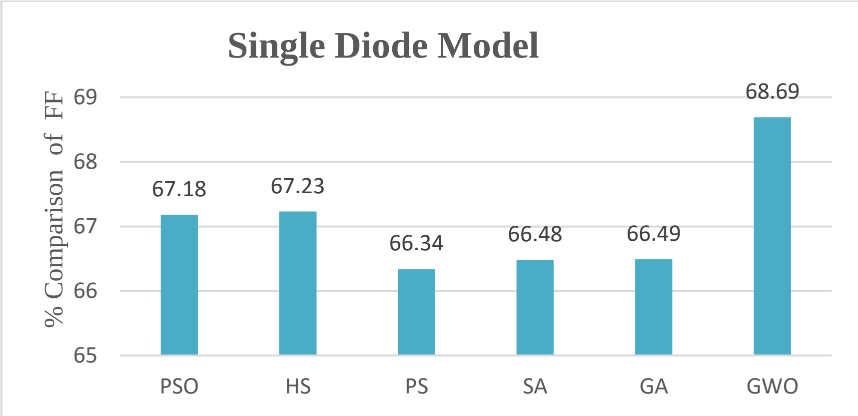


Figure 3.10. Comparison of fill-factor for SDM

GWO provides the highest values of electrical performance parameters for DDM of PV cell as shown in the Table 3.8. It is noted that the highest values of I_m, V_m and P_m as 67.66 A, 45.9 V and 31.05 W are obtained by the GWO algorithm. In addition, the other algorithms as HS achieve the second largest value while GA achieves the smallest value of performance parameters. The maximum FF value of 68.90% is achieved by GWO, which is 1.83% higher than HS, followed by PSO, GA, SA and PS as shown in Figure 3.12.

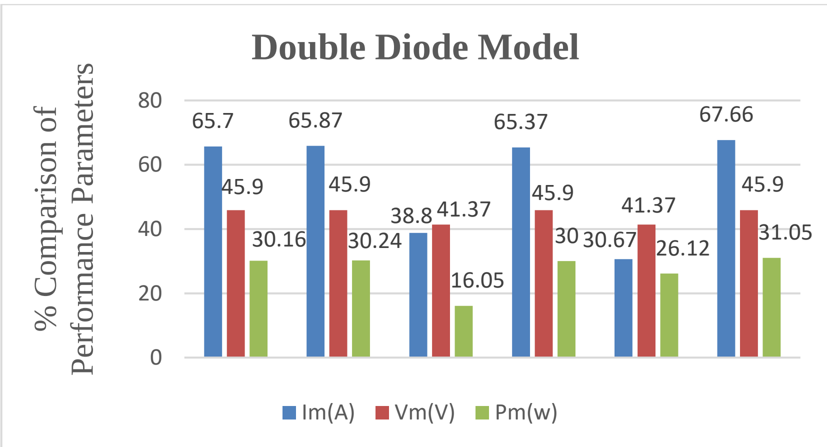


Figure 3.11. Comparison of performance parameters (I_m, V_m, P_m) for DDM

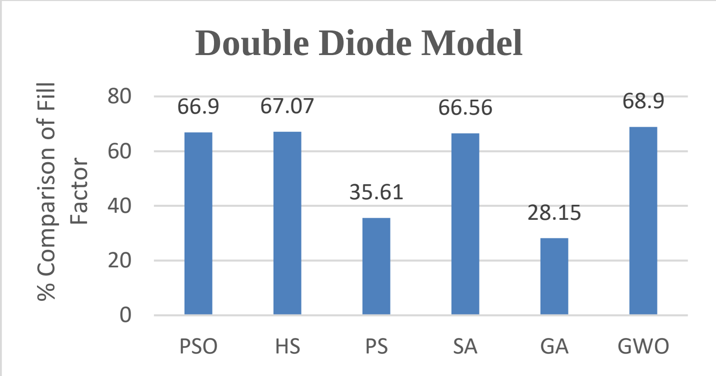


Figure 3.12. **Comparison of fill-factor for DDM**

3.5 Conclusion

In this chapter, GWO algorithm has been implemented to estimate the parameters of SDM and DDM respectively. The salient points of the study are given as follows:

- GWO is compared with five pre-existing and well-established algorithms in the literature, they are PS, SA, HS, PSO and GA.
- All the parameters i.e., five and seven parameters are extracted for SDM and DDM by using GWO algorithm and RMSE value is calculated as well as compared with other algorithms.
- Simulation results clearly indicates that the best values of estimated parameters are obtained by GWO, and RMSE is 9.4094E- 04 and 1.2450E-03 in the case of single and double diode respectively.
- Furthermore, estimated parameters obtained by GWO are compared with other algorithms in terms of electrical performance parameters such as I_m, V_m, P_m and FF.
- In the case of SDM, the best values of I_m, V_m and P_m are obtained by GWO algorithm as 67.46 A, 45.9 V and 30.96 W respectively. Moreover, GWO provided the improved FF of 1.46%.
- The highest values of I_m, V_m and P_m are achieved by the GWO algorithm as 67.66 A, 45.9 V and 31.05 W accordingly, the case of DDM. In addition to this, GWO also produced the improved FF of 1.83%.

From above discussion, it is concluded that GWO is an efficient and robust technique to estimate the unknown optimized parameters of solar PV model.

CHAPTER-4

IMPLEMENTATION OF TSA ALGORITHM FOR PARAMETER ESTIMATION OF SOLAR MODULE

4.1 Introduction

In recent years, reliance on renewable resources has increased manifold and so has the research effort to find practical solutions of problems related to expanding needs of energy, diminishing fuel reserves, a shoot-up of pollutants in air and in water, and other adverse environmental changes [1,2]. Solar energy has emerged globally as a major alternative source for energy production. Both terrestrial and roof-top photovoltaic systems are now considered as one of the common option due to its advantages of being sustainable and availability in abundance for harnessing and for conversion into electricity. Solar energy is also reflected as an extremely capable renewable resource owed to its usage and non-polluting nature [1–3]. Moreover, its modularity and scalability have added to its extensive acceptance in power systems through different PV configurations [4]. For simulating, controlling, and evaluating the PV systems, modelling of the solar cell installation must be done. Whenever PV starts operating, the solar cell parameters could be utilized for accounting the detectability and analysis [3]. Though, the practical aspect is that PV devices are majorly bare to several outer atmospheric belongings and its PV arrays didn't last always efficiently that going to harm the production of sun-based devices [4]. Accordingly, it is a critical estimation of the practical performance of PV arrays in the process to achieve, enhance, and simulate these types of systems/devices. Aiming this, we frequently use a reliable prototype to measure current and voltage files [5].

The importance of PV is estimated as a major stimulating topic by scientists/researchers and firms to progress their energy adaption and reduction of the cost [6–8]. To boost the systematic performance of PV, modelling the satisfaction of photovoltaic cells and segment is a crucial part. The non-linear dimensions and sporadic of meteorologic static make it difficult for cell constraints to identify [9]. Furthermore, the production firms require assurance of the performance of PV units for approx. twenty-five years; PV arrangements are dependent on locations and unavoidably undergo degradation along with possible occurrence of electrical faults. So, we can considerably work on a systematic model that predicts the practical behavior of the photovoltaic cell at possible working conditions [10].

Generally, PV systems are vulnerable to outside atmospheric aspects like temperature and irradiance, affecting the effectiveness of solar energy [11]. Thus, it is essential to generate current-voltage modelling setups for enhancing and controlling PV arrangements [12]. Generally, single, double, and triple diode models are majorly used for PV cells [13–15], which are extensively used to specify the cur-rent-voltage connections. Parameters of the photovoltaics help to determine the accurateness and dependability of the models. However, due to unbalanced operational cases like faults and ageing, the models' parameters are not accessible. Therefore, development of an active methodology to an accurate extract these parameters turn out to be critical. The SDM is majorly used in the approximation of their constraints because of ease and acceptance. The DDM is expected as highly accurate then SDM, especially in a lower solar irradiance, nevertheless, it desires to exist for a long consuming time [16–20]. To get more accurate and precise parameters from nonlinear implicit equations with high accuracy, evolutionary algorithms [21-31] were proposed. The bio-related algorithms are more accurate and powerful optimization algorithms to simplify nonlinear transcendental equations, as it does not include complex mathematics.

In this chapter a brief discussion is started with the problem formulation followed by a mathematical model for solar PV cell/module are presented in section 4.2. In section 4.3, a brief introduction of TSA is discussed and is implemented to estimate the optimized value of unknown parameters of a PV module model. In section 4.4, simulation results of the TSA, the algorithm is discussed and compared with pre-existing metaheuristic algorithms. Section 4.5 entails the discussion and finally, the chapter is concluded in section 4.6.

4.2 Problem Formulation

In a PV cell, the parallel circuits are formulated using a SDM and DDM. In the solar cell, the correlation between current and voltage is represented using equivalent circuit models.

4.2.1. Photovoltaic Panel Module Model

The equivalent circuit of PV panel module is shown in Figure 4.1. The relation between current and voltage at output terminal for the PV panel module is expressed as:

$$I_l/N_p = I_p - I_{SD}\left[exp\left(\frac{q\left(V_l/N_s+R_sI_l/N_p\right)}{ak_BT}\right)-1\right]-\frac{V_l/N_s+R_sI_l/N_p}{R_{sh}} \quad (4.1)$$

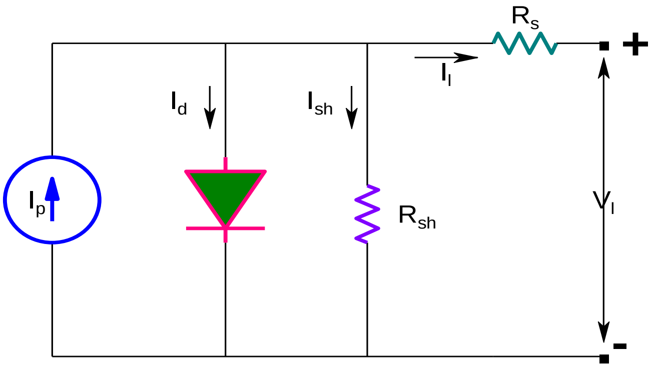


Figure 4.1. SDM of Photovoltaic Panel module

where N_s and N_p represent the number of solar cells connected in series and parallel respectively. I_l stands for cell current in output, I_p represents the photogenerated current, I_{SD} stands for reverse saturation current. V_l, a, R_s, k_B, T and q are cell output voltage, diode ideality constant, series resistance, the Boltzmann constant (1.3806503×1023 J/K), junction temperature (˚K) and the electron charge (1.60217646×10-19 °C), respectively. It is depicted in Figure 4.1 that only five parameters (I_p, I_{SD}, a, R_s and R_{sh}) are needed to be estimated for the minimum value of RMSE.

4.2.2. Objective Function

The key deliverables in this work are the optimization of unknown specification for both SDM and DDM models to reduce the error between experimental and estimated data. The objective function for error used here is the same as the authors have used previously in [23–25] as:

$$RMSE = \sqrt{\frac{1}{k}\sum_{N=1}^{k} f(V_l, I_l, \mathrm{X})^2} \quad (4.2)$$

where V_l and I_l are the measured voltage and current of the PV module. The parameter 'k' stands for the number of experimental data set. The best solution found by TSA is represented by a vector X.

For the PV panel module model,

$$\left(\begin{array}{c} f_{single}(V_l, I_l, X) = I_p - I_{SD}\left[exp\left(\frac{q\left(\frac{V_l}{N_s}+\frac{R_S I_l}{N_p}\right)}{a_1 k_B T}\right) - 1\right] - \frac{\frac{V_l}{N_s}+\frac{R_S I_l}{N_p}}{R_{sh}} - \frac{I_l}{N_p} \\ \left(X = I_p, I_{SD}, a, R_s, R_{sh}\right) \end{array} \right) \quad (4.3)$$

4.3 Tunicate Swarm algorithm

In [6], authors have proposed a new metaheuristic algorithm known as tunicate swarm algorithm. These are visible from a few meters distance creating a pale blue-green light bioluminescent which are intense in nature. These are cylindrically shaped which have to open at one end only and they grow in size of few millimeters. Each tunic consists of growing gelatinous tunic which helps to join all individuals. These tunicates have opened at one end only and they grow up too few millimeters in size. In every tunicate, a gelatinous tunic grows which help all the individuals to join. But each tunicate through atrial syphons generates jet propulsion from its opening by receiving water from the adjacent sea. To understand the actions of jet propulsion using the mathematical model the tunicate should fulfil three conditions: prevent collisions between candidate solutions, step more toward the location of the best solution, and stick close to the best solution. Figure 4.2 depicts the process flow chart of TSA for parameter extraction.

4.3.1 Prevent collisions between candidates' solutions.

Initialize the parameters $\vec{A}$ (constant), gravity force ($\vec{G}$), water flow advection in the deep ocean ($\vec{F}$), social force $\vec{M}$ and the maximum number of iterations:

$$\vec{A} = \frac{\vec{G}}{\vec{M}} \tag{4.4}$$

$$\vec{G} = c_2 + c_3 - \vec{F} \tag{4.5}$$

$$\vec{F} = 2 * c_1 \tag{4.6}$$

$$M = \lfloor P_{min} + c_1 * P_{max} - P_{min} \rfloor \tag{4.7}$$

where, c_1, c_2, c_3 are random number in the range [0,1], P_{min} and P_{max} are considered as 1 and 4.

4.3.2 Step more toward the location of the best solution.

The search agents are moved in the direction of the finest neighbors after successfully preventing a conflict with neighbors:

$$\overrightarrow{PD} = \left|\overrightarrow{FS} - rand * \vec{P}_p(x)\right| \tag{4.8}$$

where, $\overrightarrow{PD}$ is the total distance between the search agent and food source, $rand$ is the random number in the range [0,1], x indicates the current iteration, $\overrightarrow{FS}$ indicates the position of the food source, $\vec{P}_p(x)$ is the position of tunicates.

4.3.3 Stick close to the best solution.

The search agent could even establish its position as the leading search agent.

$$\vec{P}_p(x) = \begin{cases} \overrightarrow{FS} + \vec{A} * \overrightarrow{PD}, if\ rand \geq 0.5 \\ \overrightarrow{FS} - \vec{A} * \overrightarrow{PD}, if\ rand\ < 0.5 \end{cases} \tag{4.9}$$

The position of all the tunicates is updated with respect to the position of the first two tunicates as follows:

$$\vec{P}_p(x+1) = \frac{\vec{P}_p(x) + \vec{P}_p(x+1)}{2 + c_1} \tag{4.10}$$

where, $\vec{P}_p(x+1)$ represents the updated position of tunicates.

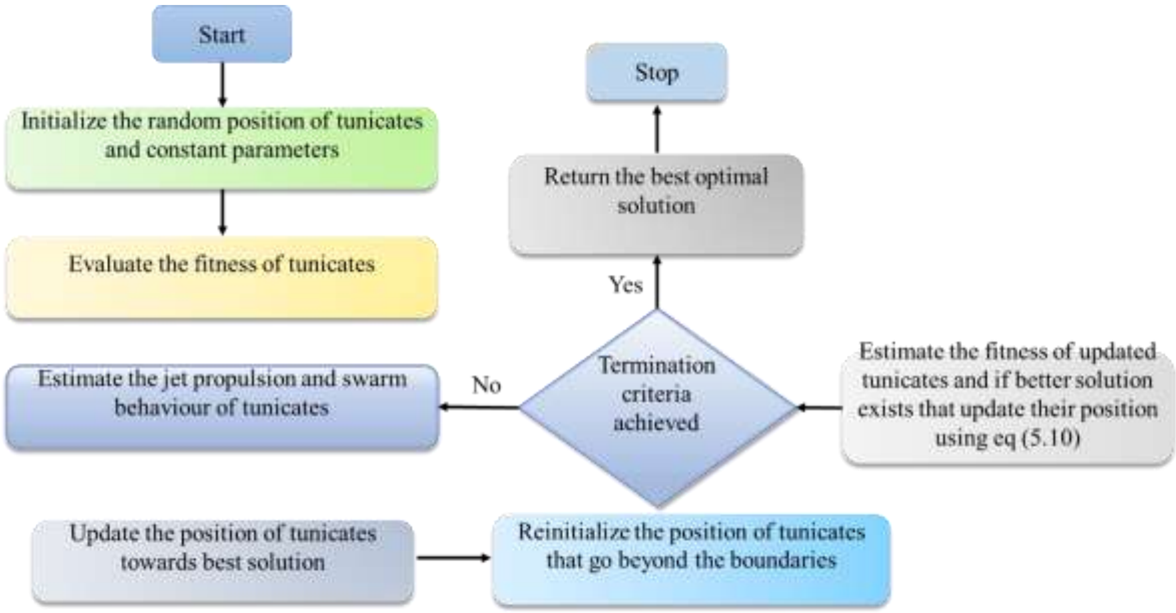


Figure 4.2. Process flow diagram of TSA

4.4 Implemenatation of TSA for parameter extraction

Step 1. Initialize the population of search agents of fifth order dimension in the search space. The fifth order dimension represents the photovoltaic current (I_p), series resistance (R_s), shunt resistance (R_{sh}), diode saturation current (I_{SD}) and diode ideality factor (a). The range of these parameters are [0-10, 0.001-2, 0-2000, 0-50, 0-100].

Step 2. Regulate the fitness of all agents in the search space using eq. (4.2).

Step 3. Update the position of the agents at every iteration using TSA. The algorithm is designed to work in the minimization mode thus the location of particles that acquire minimum cost represents the optimized parameters of SDM with minimum RMSE.

4.5 Results and Discussion

The feasibility of TSA algorithm is evaluated using mainly one PV module (Photowatt-PWP201) at STC (i.e., 1000 W/m^2 at 30°C). As a result, the retrieved PV module parameters were monitored and used to create simulated I-V data The reliability of the TSA is evaluated and compared with six meta-heuristics algorithms i.e. GSA[7], SCA [8], GWO [9], PSO [10], WOA [11], PSOGSA [12] as well as other algorithms existing in the literature. To experiment, the sample size and the objective function evaluations are set between 30 and 50,000, respectively. Furthermore, to prevent the contingency, a minimum of 30 separate runs are carried out.

The efficiency of the proposed method is evaluated based on distinct empirical tools such as the individual absolute error (IAE), the relative error (RE), the precision of the curve fitting, and the global minimum convergence patterns. The experimental values of current and voltage are taken from [13] by using Photowatt-PWP201. The Photowatt-PWP201 PV module is composed of 36 polycrystalline cells are arranged in series to generate current-voltage data under at standard temperature condition. The data collection consists of a total of 23 observations of current and voltage for the PV module. For a reasonable comparison, the search ranges (i.e. upper and lower bound) for each parameter are tabulated in Table 4.1, which are the same as those being used by investigators in [13–15]. TSA algorithm is implemented on MATLAB 2018a platform with Intel ® core ™ i7-HQ CPU, 2.4 GHz, 16 GB RAM Laptop.

Table 4.1. Range of parameters for Solar PV Module

Parameters	Photowatt-PWP201 PV Module	
	Lower Bound	**Upper Bound**
I_p(A)	0	10
I_{sd} (μA)	0	50
R_s(Ω)	0.001	2
R_{sh}(Ω)	0	2000
a	0	100

4.5.1 TSA for parameter extraction of Photowatt-PWP201 PV Module

To evaluate the efficiency of the TSA algorithm, parameters for Photowatt-PWP201 PV module were also estimated at standard temperature condition by utilizing the SDM model. The optimal value of five parameters (I_p, I_{sd}, a, R_s, R_{sh}) for SDM of the solar PV module is presented in Table 4.2. By implementing TSA algorithm under optimized parameters, the characteristics curve of current-voltage and power voltage for solar PV module is redrawn which is clearly depicted in Figure 4.3.

Table 4.2. Comparison of GWO with other parameter estimation methods for Photowatt-PWP201 PV Module

Algorithms	I_{ph} (A)	$R_s(\Omega)$	R_{sh} (Ω)	I_{sd} (μA)	a	RMSE
WOAPSO [18]	1.5032	0.0213	668.27	0.024	1.502	8.86E-04
GSA	0.0278	2	1201.097	0.050	58.4588	8.80E-03
PSOGSA	0.0218	0.6430	1100.437	0.01	79.7893	7.156E-03
SCA	1.0063	0.0496	1107.399	0.039	1.0532	1.28E-02
WOA	0.0264	0.0113	588.5011	0.0424	1.4496	9.54E-04
TSA	0.0261	0.0017	2000	0.053	1.4727	5.06E-04

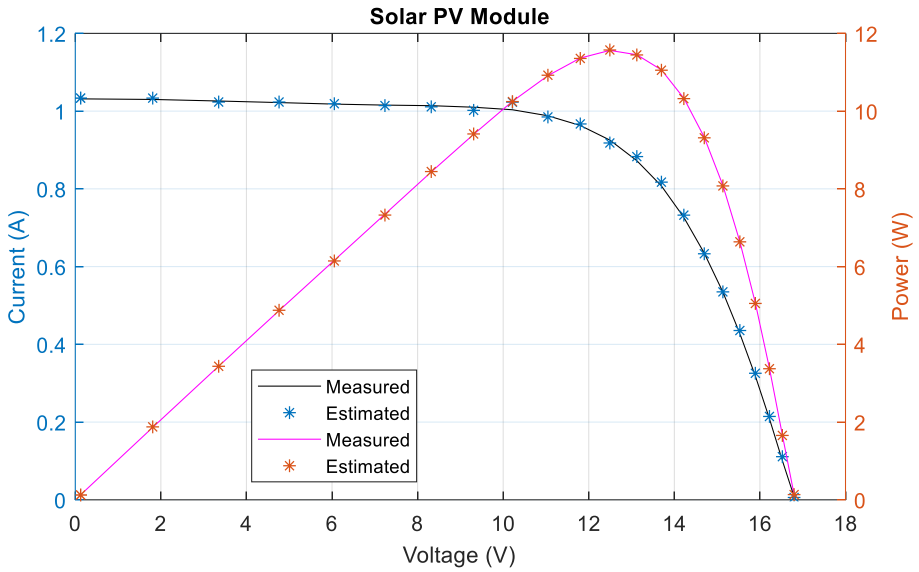
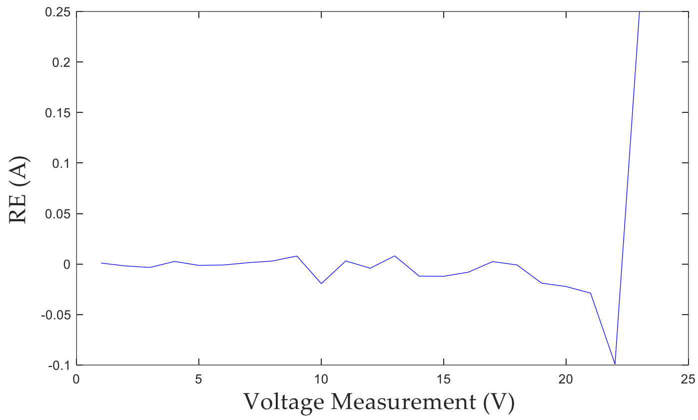


Figure 4.3. I-V and P-V characteristics curve for estimated and experimental values for single diode model of Photowatt-PWP201 PV Module

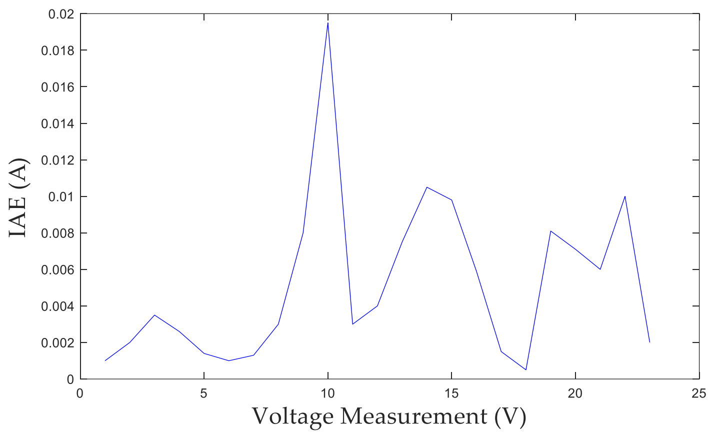
The calculated data obtained by the TSA is very effectively in coincidence with the experimental data set, all over the voltage range. Table 4.3 represents the IAE between the calculated and experimental data sets. Every determined value of IAE (at 1000 W/m^2 and 30°C) in Table 4.3 is less than 0.0195 which indicates that the parameters optimized by the TSA are very precise. The error relating the measurement results for each of 23 pair points is determined by IAE and RE, which is calculated by using Equations (4.11) and (4.12). The curve of IAE and RE between experimental and estimated values is shown in Figure 4.4.

$$IAE = |I_{measured} - I_{simulated}| \quad (4.11)$$

$$RE = \frac{(I_{measured} - I_{simulated})}{I_{measured}} \quad (4.12)$$



(a)



(b)

Figure 4.4. (a) Internal absolute error and (b) Relative error curve between measured and estimated current for Photowatt-PWP201 PV Module

Table 4.3. The calculated current and absolute error results of TSA for Solar PV Module

Observations	V_L (V)	I_L (A)	I_{sim} (A)	IAE (A)	$P_{measured}$ (W)	$P_{simulted}$(W)	IAE (W)
1	0.1246	1.0345	1.0335	0.001	0.1288	0.1256	0.0032
2	0.1248	1.0315	1.0335	0.002	0.1287	0.1226	0.0061
3	1.8093	1.03	1.0335	0.0035	1.8635	1.8765	0.013
4	3.3511	1.026	1.0234	0.0026	3.4382	3.4354	0.0028
5	4.7622	1.022	1.0234	0.0014	4.8669	4.8766	0.0097

6	6.0538	1.018	1.019	0.001	6.1627	6.1456	0.0171
7	7.2364	1.0155	1.0142	0.0013	7.3485	7.3256	0.0229
8	8.3189	1.014	1.011	0.003	8.4353	8.4453	0.01
9	9.3097	1.01	1.002	0.008	9.4027	9.4124	0.0097
10	10.2163	1.0035	1.023	0.0195	10.252	10.245	0.007
11	11.0449	0.988	0.985	0.003	10.9123	10.9234	0.0111
12	11.8018	0.963	0.967	0.004	11.3651	11.3554	0.0097
13	12.4929	0.9255	0.918	0.0075	11.5621	11.5722	0.0101
14	13.1231	0.8725	0.883	0.0105	11.4499	11.445	0.0049
15	13.6983	0.8075	0.8173	0.0098	11.0613	11.0521	0.0092
16	14.2221	0.7265	0.7324	0.0059	10.3323	10.321	0.0113
17	14.6995	0.6345	0.633	0.0015	9.3268	9.313	0.0138
18	15.1346	0.5345	0.535	0.0005	8.0894	8.0754	0.014
19	15.5311	0.4275	0.4356	0.0081	6.6395	6.6367	0.0028
20	15.8929	0.3185	0.3256	0.0071	5.0618	5.0524	0.0094
21	16.2229	0.2085	0.2145	0.006	3.3824	3.3724	0.01
22	16.5241	0.101	0.111	0.01	1.6689	1.6564	0.0125
23	16.7987	0.008	0.006	0.002	0.1343	0.1347	0.0004
Sum of IAE				0.0594			0.0927

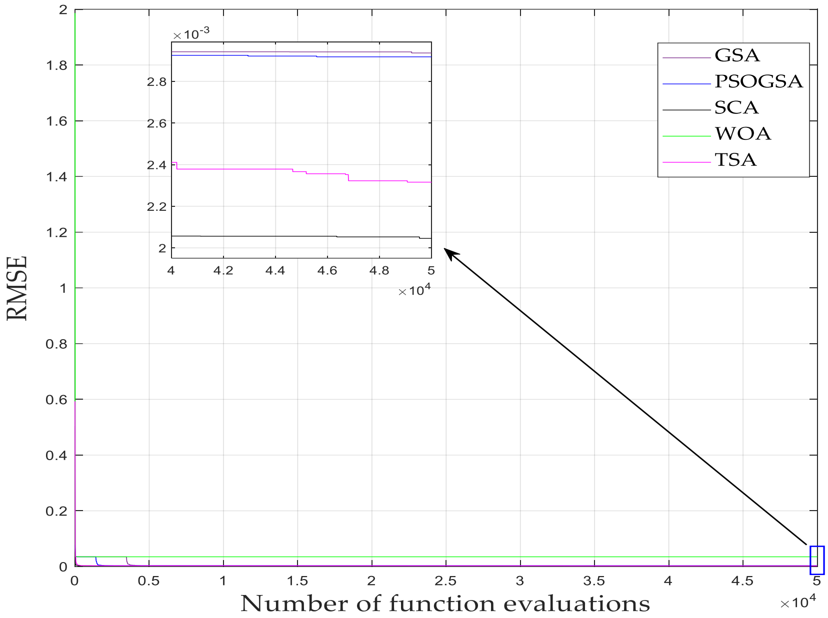


Figure 4.5. Convergence curve of TSA and other four algorithms for SDM of Photowatt-PWP201 PV Module

4.5.2 Convergence analysis

To analyze the computational competence of TSA, the convergence curves of the solar PV module is presented in Figure 4.5. It is depicted in Figure 4.5 that the TSA algorithm outperforms the GSA, PSOGSA, SCA, WOA algorithms in terms of convergence speed and generates a precise solution for the identical number of function evaluations (i.e., 50000).

4.5.3 Robustness and statistics analysis

This section presents statistical evaluation based on mean, minimum, maximum, and standard deviation of RMSE for all previously implemented methods, and comparison concerning precision and consistency of the distinct algorithms in a total of thirty runs and depicted in Table 4.4. The mean of RMSE is calculated to evaluate the precision of algorithms and the standard deviation is calculated to evaluate the consistency of the parameter estimation methods.

In Table 4.4, it is depicted that the proposed TSA algorithm significantly outperforms the GSA, PSOGSA, SCA, WOA algorithms for solar PV module model.

Table 4.4. Statistical results of RMSE of different algorithms for Photowatt-PWP201 PV Modules

	Algorithm	RMSE			
		Min	**Mean**	**Max**	**SD**
Photowatt-PWP201 module model	GSA	8.80E-03	2.65E-01	2.08E-01	5.85E-03
	PSOGSA	7.156E-03	6.47E-03	2.83E-01	1.81E-02
	SCA	1.28E-02	2.26E-01	6.35E-01	1.78E-02
	WOA	9.54E-04	2.35E-02	2.63E-01	2.83E-02
	TSA	5.06E-04	1.45E-03	2.34E-02	1.25E-03

4.6 Discussion

The TSA algorithm is successfully developed and implemented for parameter extraction of polycrystalline Photowatt-PWP201 PV module. The I-V and P-V curves obtained by the optimization process show excellent accord with the measured data. The IAE values (both current and power) validate the exactness of optimized parameters. The statistical evaluation confirms that the standard deviation is very small, which confirms that the TSA is the accurate and useful parameter estimation technique. The average execution time of every algorithm on the Photowatt-PWP201 PV module is established and introduced in Figure 4.6. Compared to GSA, PSOGSA, SCA, WOA, TSA requires a much lower time of about 11 s, while PSOGSA has the worst execution time of about 40 s. The Friedman ranking test results are shown in Figure 4.7. The best ranking is obtained by the TSA, followed by SCA, WOA, GSA and PSOGSA.

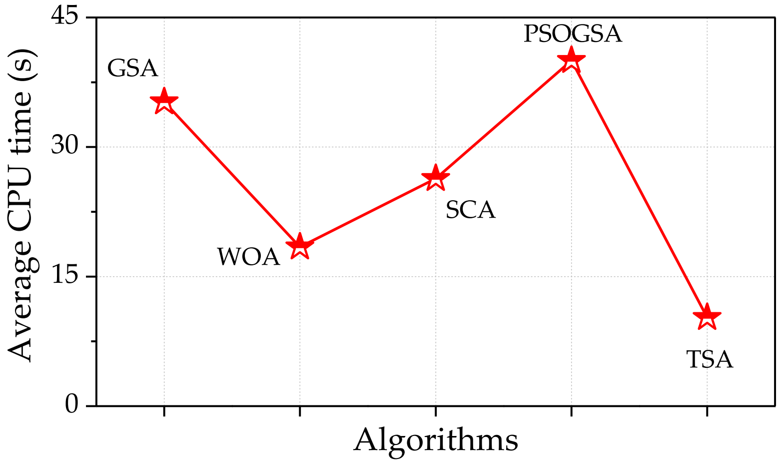


Figure 4.6. Comparison of the execution time of different metaheuristic algorithms

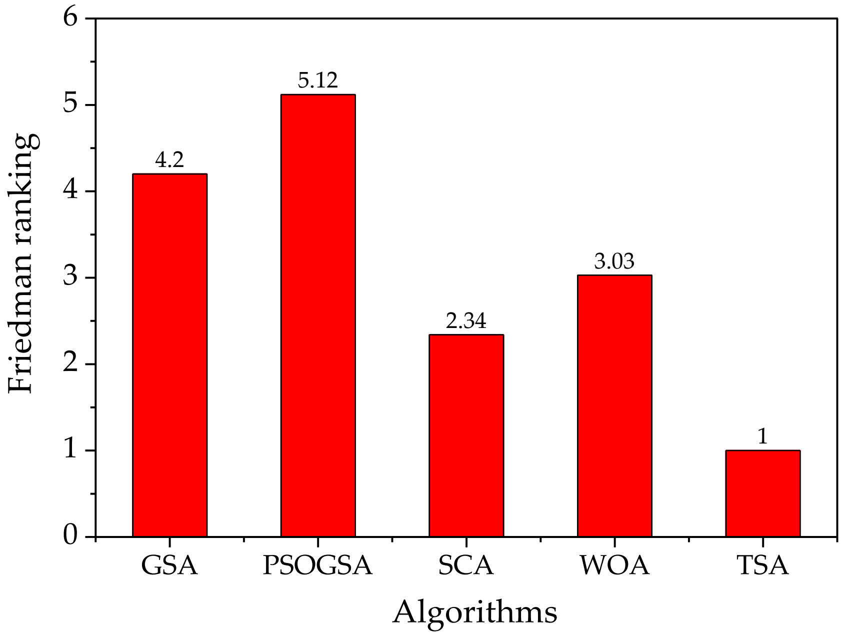


Figure 4.7. Ranking of different metaheuristics algorithms on Photowatt-PWP201 PV panel module according to the Friedman test

4.7 Conclusion

In this chapter, TSA is employed for parameter estimation of Photowatt-PWP201 PV panel module model under standard temperature conditions. It should be noted TSA technique is, for the first time, intended to reliably track the estimation of parameters for photovoltaic models. The observations based on the experimental findings are defined as follows:

- TSA is relatively accurate and reliable at delivering the solution in terms of RMSE as compared with other algorithms such as GSA, PSOGSA, SCA, and WOA.
- The I-V and P-V characteristic curves and IAE results indicate that TSA can generate the optimized value of estimated parameters for all the models of solar PV cell as compared with other algorithms.
- The statistical analysis depicts the robustness of the TSA technique on parameter estimation problem under standard operating conditions.
- The convergence curves demonstrate that the best values of estimated parameters are obtained by TSA in terms of RMSE is 5.06E-04.

From the above discussion, it can be concluded that TSA is an effective and robust technique to estimate the unknown optimized parameters of the solar PV module model at standard operating conditions.

CHAPTER-5

IMPLEMENTATION OF WOAPSO ALGORITHM FOR PARAMETER ESTIMATION OF SOLAR CELL/MODULE

5.1 *Introduction*

The depletion of fossil fuel resources, as well as the environmental impact caused by their use, necessitates the development of alternative energy resources [1]. Solar power is one of the most promising fossil fuel alternative sources. With solar photovoltaic panels, the free access to sunlight energy can be well extracted. The rapid use by the domestic and industrial sectors of solar energy makes it an essential source for study [2]. Extensive research has been conducted and the power output of the panels is improved [3, 4]. It is associated with different limitations, despite the very low operating and maintenance costs. The main limitation of solar photovoltaic power plants is the very high cost of capital for installation [5]. PV cells are having non-linear I-V and P-V characteristics with some operational limitations [6]. This non-linearity makes it difficult for any probability and approximation to increase efficiency. Only when the practical parameters (voltage current) are somewhat close to or coincide with the MPP can a PV panel operate at maximum effectiveness as defined by the manufacturer. The real behavior of PV panels rather different from the optimal conditions, due to the non-linearity of I-V characteristics of solar cells makes it essential to determine the MPP in each moment. It could be done through simulation techniques for better operational efficiency [7]. This technology is ensured by the model of the equivalent circuit having several inherent parameters. However, the parameters provided by the PV panel manufacturer don't specify the model parameters. The given information states the open-circuit voltage (V_{oc}), short circuit current (I_{sc}), and current at maximum power point (I_{mpp}) under standard test conditions (i.e., 1000 W/m^2, 25°C). Practical parameters vary at all times as the weather changes. The ageing effects of PV also change the circuit parameters [3, 8, 9].

The PV system's core unit is a solar cell, and the parameters for a close analysis of the performance of the panel around its MPP must be extracted from the most urgent issue. The combined simulation study of cells provides the performance analysis of whole PV panels [8, 10]. The equivalent circuit for the SDM and DDM for parameter extraction is the recent and most widely used approach. The method of parameter extraction can be bifurcated into two major categories: analytical and optimization methods [11-15]. Although the analytical methods are the simplest and yields result quickly, but it misses the accuracy under normal day conditions with variable lighting. The deterministic ways of parameter extraction such as Newton- Raphson, non-linear least square, Lambert W-functions [16], Iterative curve fitting [17], conductivity method [18], Levenberg-Marquardt algorithm [19], are having many boundaries such as continuity, differentiability, and convexity related to objective functions. The boundary conditions further restrict the use of the above analytical methods, because in the case of multimodal optimization problems local minima is obtained. Therefore, methods of analysis are not sufficient for parameters to be extracted.

To get more accurate and precise parameters from nonlinear implicit equations with high accuracy, evolutionary algorithms [20] were proposed. The bio-related algorithms are more precise and potent optimization algorithms that simplify transcendental nonlinear equations, since complex mathematics are not presented there. However, researchers developed a number of metaheuristic algorithms, but there's no algorithm that gives the best solution to all problems, as NFL theorem has stated. This has motivated researchers to design new algorithms to efficiently solve complex science and engineering problems. Gradient based optimizer (GBO) [20] inspired from gradient based Newton's method, Harris-Hawk optimizer (HHO) [21] inspired from cooperative behavior and chasing style of Harris' Hawks, Heap-based optimizer (HBO) [22] inspired from corporate rank hierarchy and slime mould algorithm (SMA) [23] inspired from diffusion and foraging conduct of slime mould are some of the recently developed metaheuristic algorithms. Some of the recent optimization algorithms used for the parameter extraction are GA [24], DE [25], SA [26], PS [27], HS [28], CS [29], FPA [30], bacterial foraging optimization (BFO) [31], bird mating [32], artificial bee swarm optimization (ABSO) [33]. Premature convergence problems are associated with the proposed algorithms. The main disadvantage of GA is that it has large search space for the parameter optimization, which complicates and slows the system. PSO was used to overcome the problem of large search spaces. However, it imposed the problem of the randomly chosen initial parameter value. The value exchange in SA between the cooling timetable and the original temperature makes it less popular. There is a likelihood that PSO will choose an incorrect pattern, leading to premature convergence or no convergence. PSO with reverse barrier restriction for series resistance (R_s), shunt resistance (R_{sh}), and diode ideality factor (a) is suggested for fast and coherent convergence of optimization issue to global optima, considering the temperature impact to reduce the modeling errors in DE [31]. Although the BFO technique offers excellent outcomes but involving too many parameters that have complicated the scheme and imposed a computational strain. A hybridization approach is carried out by the researchers in [34] for parameter extraction of solar PV cell. In this approach hybridization of two algorithms: firefly and PS are implemented. The exploration phase is completed by the firefly algorithm during the first half iteration and then the pattern search algorithm takes control of the population for the exploitation phase. A new OBL approach is incorporated with whale optimization and shuffled complex evolutionary algorithm for optimization of solar cell parameters [35, 36]. This approach is tested on unimodal as well as on multimodal benchmark functions and simulation results clearly show the robustness of the algorithms.

WOA [37] and PSO [38] are the two most prominent used metaheuristics techniques as available in the literature. However, they differ from each other in the search mechanism for the best solution in a defined search space. WOA mimics the social behavior of humpback whales while PSO mimics the searching behavior of the birds in a group. It is shown by many previous research studies that WOA is good at exploring [39] the search space but suffers from slow convergence rate due to low exploitation ability while PSO don't have good capability in exploring [40] the search space but have good local search capability. In [41], author proposed chaotic WOA (CWOA) to improve maps utilized their dynamic behavior to prevent an optimization algorithm to trap in local optima and improves its global search capability. In [42] author proposed Levy flight trajectory based WOA (LWOA) to improve the accuracy and convergence speed of the algorithm. Levy flight allows the algorithm to get rid of local optima and prevents premature convergence. There are certain complex and non-convex optimization problems that are not solved by continuous metaheuristic therefore in [43] author proposed binary WOA (BWOA). In [44] author proposed a modified WOA that includes whale memory and new random search agent to enhance the exploitation capability of the algorithm. In [45] author improved the exploration capability of WOA and proposed three modified WOA which are based on OBL, exponentially decreasing parameters, and re-initialization of worst particles. Hybridization of metaheuristic algorithms is another approach to improve the exploration and exploitation capability of population based stochastic algorithm. Furthermore, researchers have proposed hybrid approach grey wolf optimization (HAGWO) [46], colliding bodies optimization WOA (CBO-WOA) [47], memetic-WOA (MWOA) [48], simulated annealing WOA (SAWOA) [39], moth flame (MFOWOA) [49], Sine-Cosine (SC-WOA) [50], pattern search WOA (PS-WOA) [51], Brain Storm (BS-WOA) [52] to improve the global and local search capability of WOA. According to the literature survey WOAPSO has not been implemented yet for the parameter extraction of the solar cell (and it cannot be used to establish a PV parameter estimation technique that can overcome all existing techniques). Therefore, the main aim of this chapter is to anticipate a new parameter estimation algorithm for solar cell/module.

5.1.1 Novelty of Work

The main contribution of the proposed study can be described as follows:

- A hybrid version of WOAPSO algorithm is proposed for parameter extractions of solar cell/module.
- The exploitation capability of WOA is significantly improved by incorporating the exploitation capability of PSO with adaptive weight in sequential mode. As a result, equivalent circuit parameters are converging equally good to the true values with minimum error.

- The performance of proposed WOAPSO algorithm is measured based on convergence analysis, robustness, reliability, and statistics analysis for three PV models at diverse operating conditions and compared with the previous algorithms existing in the literature.

The organization of this chapter is as follows: the problem formulation and mathematical model for solar PV cell/module are presented in section 5.2. In section 5.3 a brief introduction of WOA, PSO, and proposed WOAPSO algorithm and discussed its implementation to estimate the optimized value of unknown parameters of a single diode, double diode, and PV module model. In section 5.4 simulation results of the WOAPSO algorithm are discussed and compared with pre-existing metaheuristic algorithms. Finally, section 5.5 provides a conclusive remark to summarize the chapter.

5.2 Problem Formulation

In this section, the equivalent circuits of a photovoltaic solar cell are formulated using SDM and DDM. These equivalent circuit models are used to describe the current-voltage characteristics of a solar cell.

5.2.1 PV panel model

The equivalent circuit of PV panel module is shown in Figure 5.1. The relation between current and voltage at output terminal for the PV panel module is expressed as:

$$\mathrm{I_l/N_p = I_p - I_{SD}\left[\exp\left(\frac{q\left(V_l/N_s + R_s I_l/N_p\right)}{a_1 k_B T}\right) - 1\right] - \frac{V_l/N_s + R_s I_l/N_p}{R_{sh}}} \tag{5.1}$$

where N_s and N_p represents the number of solar cells connected in series and parallel respectively. It is clearly depicted from Figure 5.1 that only five parameters (I_p, I_{SD}, a_1, R_s *and* R_{sh}) are needed to be estimated for minimum value of RMSE.

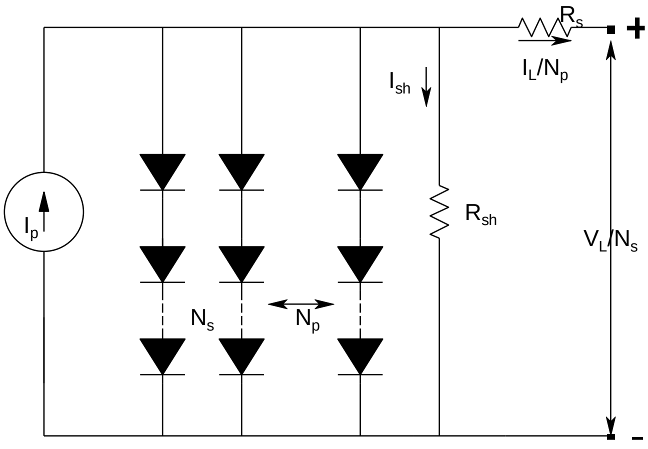


Figure 5.1. Equivalent circuit of PV panel module model

5.2.2 Objective function

The key purpose of this work is to optimize the unknown parameters for both the models (SDM and DDM) and to reduce the error between experimental and estimated data. The objective function for error used here is same as the authors have used previously in [91-93] as:

$$RMSE = \sqrt{\frac{1}{k}\sum_{N=1}^{k} f(V_l, I_l, \mathrm{X})^2} \quad (5.2)$$

where, V_l and I_l are the measured voltage and current of PV module. The parameter 'k' stands for the number of experimental data set. The best solution found by WOAPSO is represented by a vector X. For the SDM:

$$\begin{cases} f_{single}(V_l, I_l, X) = I_p\text{-}I_{SD}\left[exp\left(\dfrac{q(V_l + I_l R_s)}{a_1 k_B T}\right)\text{-}1\right]\text{-}\dfrac{V_l + I_l R_s}{R_{sh}}\text{-}I_l \\ \qquad\qquad (X = I_p, I_{SD}, a_1, R_s, R_{sh}) \end{cases} \quad (5.3)$$

For the double diode model:

$$\begin{cases} \mathrm{f_{double}}(\mathrm{V_l}, \mathrm{I_l}, \mathrm{X}) = \mathrm{I_p} - \mathrm{I_{SD1}}\left[\exp\left(\dfrac{\mathrm{q(V_l + I_l R_s)}}{\mathrm{a_1 k_B T}}\right) - 1\right] \\ \quad -\mathrm{I_{SD2}}\left[\exp\left(\dfrac{\mathrm{q(V_l + I_l R_s)}}{\mathrm{a_2 k_B T}}\right) - 1\right] - \dfrac{\mathrm{V_l + I_l R_s}}{\mathrm{R_{sh}}} - \mathrm{I_l} \\ \qquad (\mathrm{X} = \mathrm{I_p}, \mathrm{I_{SD1}}, \mathrm{I_{SD2}}, \mathrm{a_1}, \mathrm{a_2}, \mathrm{R_s}, \mathrm{R_{sh}}) \end{cases} \quad (5.4)$$

For the PV panel module model:

$$\begin{cases} f_{module}(V_l, I_l, X) = I_p - I_{SD}\left[\exp\left(\dfrac{q\left(\dfrac{V_l}{N_s}+\dfrac{R_s I_l}{N_p}\right)}{a_1 k_B T}\right)-1\right] \\ \qquad - \dfrac{V_l/N_s + R_s I_l/N_p}{R_{sh}} - I_l/N_p \\ \qquad (X = I_p, I_{SD}, a_1, R_s, R_{sh}) \end{cases} \tag{5.5}$$

5.3 WOAPSO algorithm

The hybridization of metaheuristic algorithm plays a vital role in improving their performance. The fundamental principle of hybridization is to blend the best features of two or more metaheuristic algorithms to improve search capability, accuracy, and convergence speed of an individual algorithm. A hybrid algorithm is also known as a memetic algorithm. In the last few years, researchers have proposed different strategies for hybridizing metaheuristic algorithms. The three most explored methodologies of hybridization are multi-stage, sequential and parallel [94].

In multi-stage one of the algorithms globally explores the search space and the second algorithm locally discovers the optimal solution. In sequential search both the algorithms run sequentially and find the optimal solution in the search space. In the parallel mode both the algorithms run parallel on the same population of the defined problem.

5.3.1 Particle swarm optimization (PSO)

PSO [95] is a nature inspired stochastic optimization technique proposed by J. Kennedy and R. C. Eberhard in 1995. It is a population based computationally inexpensive technique that is inspired by the social behavior of fish schooling and bird flocking. The methodology of the algorithm is that swarm of particles fly in the search space and finds the optimal solution by updating their own best solution and the best solution obtained by the swarms. The swarm is randomly initialized as particles in N-dimensional search space with position x_i and velocity v_i. The position of the particles represents the probable solution, and the velocity represents the rate of change of position of the particle concerning the current position. The particles change their positions with respect to the positions of the best particle. The velocity update equations are given by:

$$v_i^d(t+1) = w * v_i^d(t) + c_1 * r_1 * \left(pbest_i^d(t) - x_i^d(t)\right) + c_2 * r_2 * \left(gbest^d - x_i^d\right) \quad (5.6)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad (5.7)$$

where, v_i^d(t) and $x_i^d(t)$represents the velocity and position of ith particle in dth dimension at t[th] iteration, $v_i^d(t+1)$ and $x_i^d(t+1)$is the velocity and position of the i[th] particle in d[th] dimension at (t+1)[th] iteration. $pbest_i^d$ represents the current best position of the particles and $gbest^d$represents the best position among all the particles in dth dimension, c_1 and c_2 are the acceleration parameter, r_1 and r_2 are the random number in the range [0,1] and w is the inertial weight vector which maintains balance between exploration and exploitation.

5.3.2 Whale optimization algorithm (WOA)

Whale optimization algorithm is a population-based optimization algorithm which mimics the social behavior of humpback whales and is proposed by Mirjalili and Lewis in 2016 [22]. Humpback whales are long in size and have an interesting food searching capability, they attack their prey (krill and small fishes) by bubble-net hunting strategy. WOA is inspired by this hunting behavior and works in three phases first it searches for prey then encircle prey and lastly attack the prey. Humpback whales swim around the prey either following a shrinking path or through a spiral movement. A probability factor *p* assumed to be 50% simultaneously choose either of the two movements.

(A) Shrinking movement

Initially in the exploration phase humpback whales search around a prey chosen randomly in the search space with the following mathematical model:

$$\vec{D} = \left|\vec{C} * \vec{X}_{rand} - \vec{X}\right| \quad (5.8)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} * \vec{D} \tag{5.9}$$

where, t is the current iteration and (t+1)th is the next iteration, $\vec{X}_{rand}$ is the random position of the prey, $\vec{A}$ and $\vec{C}$ are the coefficient vectors and is defined as:

$$\vec{A} = 2\vec{a}\vec{r} - \vec{a} \tag{5.10}$$

$$\vec{C} = 2 * \vec{r} \tag{5.11}$$

where, $\vec{a}$ is decreased from 2 to 0 over the course of iterations and $\vec{r}$ is the random number in the range [0,1]. In the exploitation phase the position of whales are updated based on the position of the best search prey $\vec{X}^*$. Mathematically it is defined as:

$$\vec{D} = \left|\vec{C} * \vec{X}^* - \vec{X}\right| \tag{5.12}$$

$$\vec{X}(t+1) = \vec{X}^* - \vec{A} * \vec{D} \tag{5.13}$$

(B) Spiral movement

In the spiral movement of the humpback whale, first the distance is evaluated between the whale located at (X, Y) and best search prey located at (X*, Y*). Once the distance is evaluated then the helix-shaped movement of whale around the prey is defined with following mathematical equation:

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \tag{5.14}$$

where, $\vec{D}' = \left|\vec{X}^*(t) - \vec{X}(t)\right|$ is the distance between the whale and best searched prey, *b* is the constant which maintains the shape of the logarithmic spiral and l is the random number defined in the range [-1,1].

In WOA, coefficient vector 'A' maintains the balance in exploration and exploitation, when the value of $p<0.5$ and $A>1$then the positions are updated by eq. (5.9) and (5.13) while when $p<0.5$ and $A<1$ the positions are updated by eq. (5.13) and (5.14) and when the $p\geq 0.5$ then the positions are updated using eq. (5.14).

5.3.3 Hybrid WOAPSO algorithm

In this section, the principle of the proposed hybrid WOAPSO algorithm is briefly addressed. In general performance of any optimization technique while solving any NP problem is affected by premature convergence and slow rate of convergence. Some algorithms better explore the search space and have a slow convergence rate while some algorithms less diversely explore the search space and didn't find the optimal solution. Maintaining the balance between exploration and exploitation is a critical issue in any optimization algorithm. WOA has good exploration capability but exploitation depends on evaluating the distance between the whale and the best position of the prey [96] and if the distance is large then it takes more time to converge [97]. While PSO has fast rate of convergence but it is prone to premature convergence due to weakness in global search capability [98]. Since in PSO if the global best solution gets trapped in local optima, then the rest of the particles don't explore the search space and follow the global best solution and they all get trapped in local optima. Therefore, it can be concluded that WOA is good at exploring the search space but suffers from a slow convergence rate while PSO doesn't have good capability in exploring the search space but have good local search capability. The aim of the proposed hybrid algorithm is to enhance the exploitation capability of WOA by embedding the PSO algorithm to find an optimal solution around the region explored by WOA. The proposed approach is mixed, co-evolutionary in which PSO is used as a component of WOA and thus the hybrid approach utilizes the strength of both the algorithms to avoid the premature convergence and local optima. The mathematical model of the proposed algorithm is illustrated in the following steps:

Step 1: Initialize the random population of search agents with position and velocity defined as:

$$X_i = \left(x_i^1, \dots\dots\dots\dots . x_i^d, \dots\dots\dots . x_i^n\right), for = 1,2, \dots\dots\dots\dots . N \tag{5.15}$$

$$V_i = \left(v_i^1, \dots \dots \dots \dots . v_i^d, \dots \dots \dots . v_i^n\right), for\ i = 1,2, \dots \dots \dots \dots . N \qquad (5.16)$$

Step 2: Calculate the fitness of each search agent. If the problem is the minimization problem, then $\vec{X}^*$ is the position corresponding to the minimum fitness and for maximization problem $\vec{X}^*$ is the position corresponding to the maximum fitness. $\vec{X}^*$ is the best search agent.

Step 3: Update the constant parameters A, C, using eq. (5.10) and (5.11) and l lying between [-1,1] and p is the probability between 0 and 1.

Step 4: If p<0.5 and |A|≥1, then select the random position of search agent (X*) in search space and update the position of search agent using eq. (5.9) and (5.13).

elseif p<0.5 and |A|<1, then update the position of search agent using eq. (5.13) and (5.14) .

else p>0.5, then update the position of search agent using eq. (5.14).

Step 5: Update the velocity of search agent based on the best position of search agent (X*) in the search space using the following equation:

$$v_i^d(t+1) = w * v_i^d(t) + c_1 * r_1 * \left(X^* - x_i^d(t)\right) \qquad (5.17)$$

Step 6: Update the position of the particles using eq. (5.17).

Step 7: Go to step 3 until the termination criteria is met. The algorithm terminates when either maximum number of iterations or minimum error criteria is attained.

Step 8: In the last iteration the returned value of $\vec{X}^*$ represents the global minimum and the position corresponding to it represents the solution of the problem.

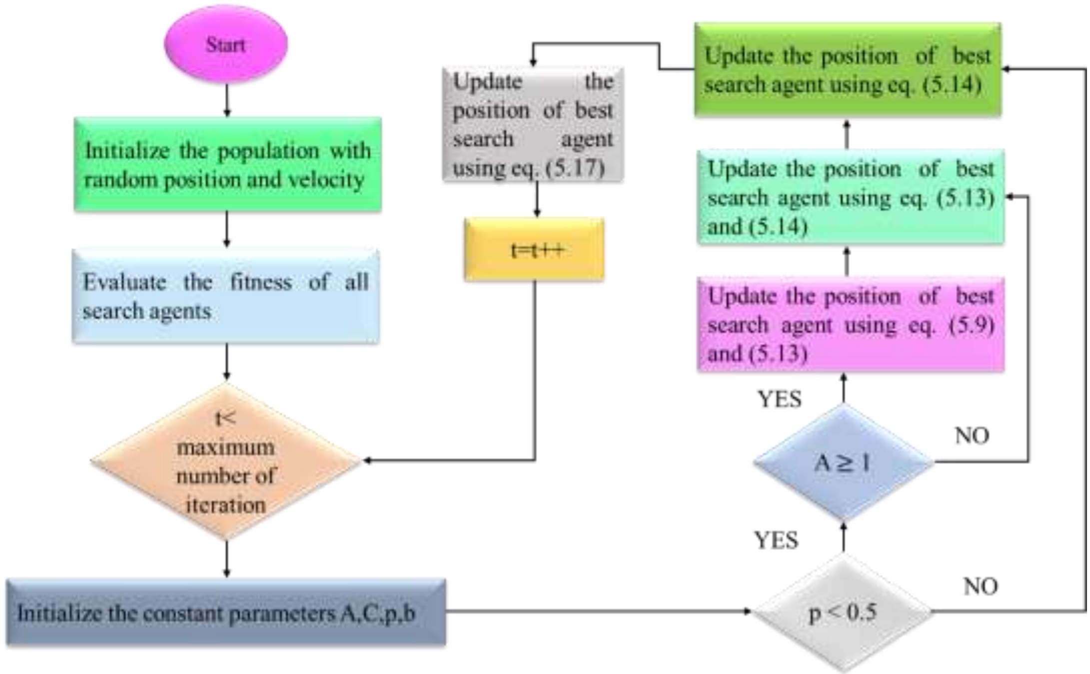


Figure 5.2. Flowchart of proposed WOAPSO algorithm

5.3.4 Implementation of WOAPSO for parameter extraction

5.3.4.1 Single-Diode Model

- Initialize the population of search agents of fifth order dimension in the search space. The fifth order dimension represents the photovoltaic current (I_p), series resistance (R_s), shunt resistance (R_{sh}), diode saturation current (I_{SD}) and diode ideality factor (a_1). The range of these parameters are [0-1, 0.001-0.5, 0-100, 0.01-0.5, 1-2].
- Regulate the fitness of all agents in the search space using eq. (5.3).
- Update the position of the agents at every iteration using WOAPSO. The algorithm is designed to work in the minimization mode thus the location of particles that acquire minimum cost represents the optimized parameters of SDM with minimum RMSE.

5.3.4.2 Double-Diode Model

- Initialize population of search agents of seventh order dimension in the search space. The seventh order dimension represents the photovoltaic current (I_p), series resistance (R_s), shunt resistance (R_{sh}), diode saturation currents (I_{SD}, I_{SD1}) and diode ideality factor (a_1, a_2). The range of these parameters are [0-1, 0.001-0.5, 0-100, 0.01-0.5, 0.01-0.5, 1-2, 1-2].

- Regulate the fitness of all agents in the search space using eq. (5.4).
- Update the position of all agents at every iteration using WOAPSO. The algorithm is designed to work in the minimization mode thus the location of particles having minimum cost represents the parameters of DDM with minimum RMSE.

5.4 Results and Discussion

In this section, the feasibility of the proposed new hybrid WOAPSO was tested and evaluated using mainly two types of PV devices: one PV cell (R.T.C France solar cell) and one PV module (SS2018P) at different solar irradiation. As a result, the retrieved PV cell and module parameters were monitored and used to create simulated I-V data for each device type. The accuracy and reliability of the WOAPSO were assessed by comparing the techniques published in the literature with the existing art. The efficiency of the proposed method is evaluated based on distinct empirical tools such as IAE, RE, the precision of the curve fitting, and the global minimum convergence patterns. The experimental values of current and voltage are taken from [55] by using R.T.C France solar cell at standard temperature condition i.e., 1000 W/m^2 at 33°C. The SS2018P PV module is composed of 36 polycrystalline cells connected in series and generate the I-V data under different irradiance levels i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2 and 630 W/m^2. The data collection consists of a total of 20 I-V measurements for solar cell and 27 for PV module. The values of current and voltage for solar PV module (SS2018P) are measured across variable resistive load (0.1- 250 Ω, 2A). The measured value of voltage and current at different irradiance level is presented in Table A1 (appendix). For a reasonable comparison, the search ranges (i.e., upper and lower bound) for each parameter are tabulated in Table 5.1, which are the same as those being used by investigators in [27]. The proposed WOAPSO algorithm is implemented on MATLAB 2018a platform with Intel ® core ™ i7-HQ CPU, 2.4 GHz, 16 GB RAM Laptop. To evaluate the reliability of the WOAPSO, it is compared with six well established metaheuristics algorithms i.e., GSA [56], SCA [57], GWO [58], PSO [59], WOA [37], PSOGSA [60] as well as other algorithms existing in the literature. In order to conduct the experiment, the sample size, and the estimated number of objective function evaluations are set at 30 and 50,000, respectively. Furthermore, to prevent the contingency, a minimum of 30 separate runs are carried out.

Table 5.1. **Range of parameters for SDM, DDM and PV Module**

Parameter	SDM/DDM		SS2018P PV Module	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
I_p(A)	0	1	0	10
I_{sd}, I_{sd1}(μA)	0.01	0.5	0	50
R_s(Ω)	0.001	0.5	0.001	2
R_{sh}(Ω)	0	100	0	2000
a, a_1, a_2	1	2	0	100

5.4.1 Parameter estimation of Single Diode Model using WOAPSO

For the case of SDM only five parameters i.e., I_p, I_{sd}, a, R_s, R_{sh} are required to be estimated. Table 5.2 signifies the values of parameters optimized by WOAPSO and RMSE, for the comparison. It can be depicted that WOAPSO generates the least RMSE of 7.1700E-04, which is very small compared to the performance of the other six algorithms: GSA, SCA, GWO, PSO, WOA, PSOGSA, and pre-existing algorithms (Table A2, provided in appendix) available in literature. Here RMSE values are acquired as the index for the evaluation of results with previously existing algorithms implemented by the researchers.

Table 5.2. **Comparison of WOAPSO with different parameter estimation methods for SDM**

Algorithms	I_{ph}(A) ± SD	I_{sd} (μA) ± SD	R_s (Ω) ± SD	R_{sh} (Ω) ± SD	a± SD	RMSE
GSA	0.7607±0.0053	0.05±0.0265	0.0339±0.0076	63.7784±4.304	1.5486±0.0042	1.2012E-03

SCA	0.7595±0.0209	0.002±0.034	0.0519±0.0229	90.0685±4.517	1.2641±0.140	1.9123E-03
GWO	0.7695±0.0038	1±0.193	0.0269±0.0037	47.9136±16.872	1.6232±0.0311	9.4095E-04
PSO	0.7383±0.023	1±0.023	0.0501±0.0053	25.1251±3.213	1.6605±0.024	1.4320E-03
WOA	0.7573±0.0019	0.016±0.0056	0.053±0.0028	58.5839±0.354	1.2476±0.0043	9.9529E-04
PSOGSA	0.7677±0.0071	0.01±0.006	0.0522±0.0066	18.4587±37.62	1.218±0.0349	1.2400E-03
WOAPSO	0.7597±0.0012	0.499±0.004	0.0342±0.0007	83.0131±0.027	1.5483±0.001	**7.1700E-04**

The characteristics curve of current-voltage and power-voltage for SDM is redrawn based on the best optimized parameters obtained by implementing the WOAPSO algorithm and depicted in Figure 5.3. It is depicted in Figure 5.3, that calculated data obtained by the WOAPSO is very effectively in coincidence with the experimental data set, under S.T.C (i.e., 1000 w/m^2 and 33°C), all over the voltage range. Table A3 (Appendix) represents IAE between the calculated and experimental data sets. Every determined value of IAE in Table A3 is less than 0.0018 which indicates that the parameters optimized by the WOAPSO are very precise. The error relating the measurement results for each of 20 pair points is determined by IAE and RE, which is calculated by using eq. (5.18) and (5.19) respectively. The curve of IAE and RE between experimental and estimated values is shown in Figure 5.6.

$$IAE = |I_{measured} - I_{simulated}| \tag{5.18}$$

$$RE = (I_{measured} - I_{simulated})/I_{measured} \tag{5.19}$$

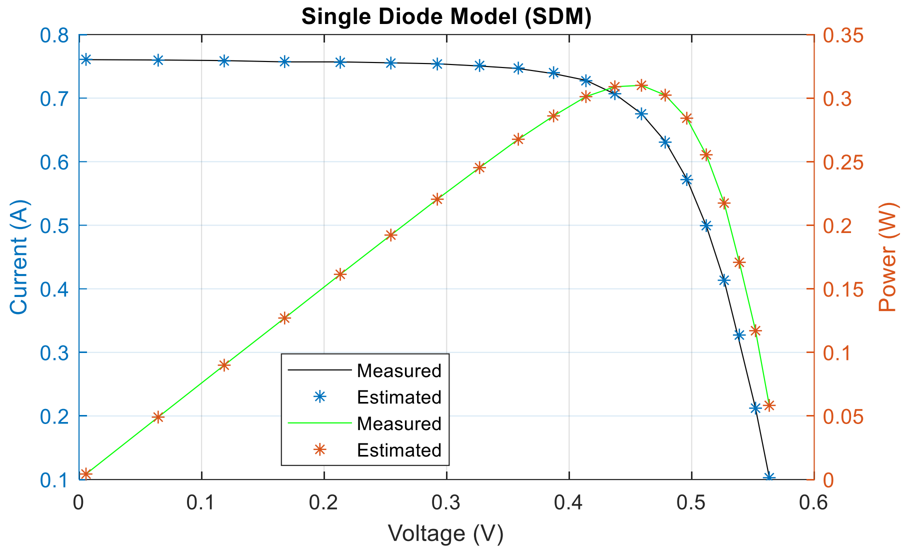


Figure 5.3. I-V and P-V characteristics curve for estimated and experimental values for SDM of R.T.C France solar cell

5.4.2 WOAPSO for parameter estimation of Double Diode Model

In the case of DDM, there are basically seven parameters (I_p, I_{sd}, I_{sd1}, a_1, a_2, R_s, R_{sh}) which are required to be optimized. The values of optimized parameters and minimum of RMSE are presented in Table 5.3, for the comparison. It is analyzed from Table A4 (appendix), MLBSA (9.8249E-04), EHHO (9.8360E-04), IJAYA (9.8293E-04) and GOTLBO (9.8317E-04) produces the best value in terms of RMSE, while WOAPSO generates the third-best value of RMSE (9.8412E-04) which is very close to MLBSA, EHHO, IJAYA and GOTLBO. However, the computational cost in terms of function evaluation is 1/3 of MLBSA, EHHO, IJAYA and GOTLBO. Moreover, WOAPSO shows the superiority over other algorithms in terms of RMSE. The characteristics curve in terms of current-voltage and power-voltage for the DDM is redrawn based on the best optimized parameters.

Table 5.3. Comparison of WOAPSO with different parameter estimation methods for DDM

Algorithms	I_{ph}(A)±SD	I_{sd1}(μA) ± SD	I_{sd2}(μA)± SD	R_s (Ω)± SD	R_{sh} (Ω)± SD	a_1± SD	a_2± SD	RMSE
GSA	0.7641±0.0079	0.05±0.177	0.001±0.1191	0.0344±0.0091	37.780±1.21	1.9943±0.1756	1.5492±0.1076	2.03E-03
SCA	0.7623±0.0097	0.0012±0.059	0.001±0.046	0.0595±0.0067	52.4903±24.02	2±0.3030	1.2197±0.2088	3.18E-03

GWO	0.7609±0 .0026	0.3156± 0.0052	0.0001± 0.008	0.0323± 0.0015	65.6799± 6.5859	1.9426± 0.0625	1.5312± 0.0272	1.60E-03
PSO	0.7676±0 .0016	0.0216± 0.027	0.0947± 0.234	0.0335± 0.012	54.9501± 5.4630	1.4606± 0.203	1.8363± 0.0137	2.90E-03
WOA	0.76354± 0.0019	0.169±0. 0017	0.163±0 .0011	0.0410± 0.0022	35.7342± 0.7539	2±0.034	1.4420± 0.0036	4.30E-03
PSOG SA	0.7611±0 .0041	0.432±0. 0171	0.01±0. 0021	0.0347± 0.0042	61.72±18 .7135	1.9±0.01 83	1.5489± 0.0144	1.48E-01
WOA PSO	0.7601±0 .0007	0.5±0.00 20	0.5±0.0 027	0.0311± 0.0005	100±0.43 45	1.5755± 0.0043	1.7314± 0.0015	**9.8412 E-04**

The values of IAE are depicted in Table A5 (Appendix). From Figure 5.4, it can be projected that the estimated data based on optimized parameters are in high coincidence with the experimental data set. From Table A5, it can be easily analyzed that all the values of IAE are less than 0.0097, which demonstrates the accuracy of optimized parameters produced by WOAPSO. The error relating the measurement results for each of 20 pair points is determined by IAE and RE, which is calculated by using eq. (5.18) and (5.19) respectively.

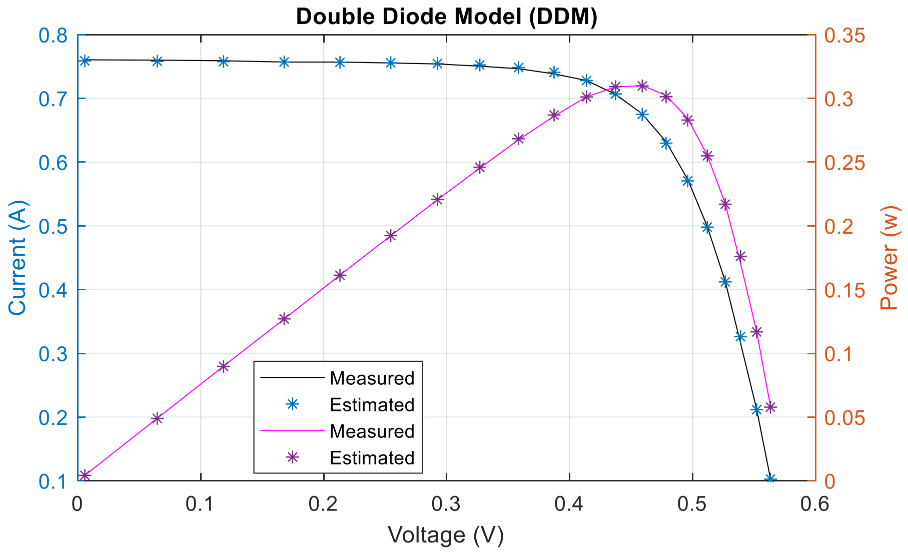


Figure 5.4. I-V and P-V characteristics curve for estimated and experimental values for DDM of R.T.C France solar cell

5.4.3 WOAPSO for parameter estimation of SS2018P PV Module

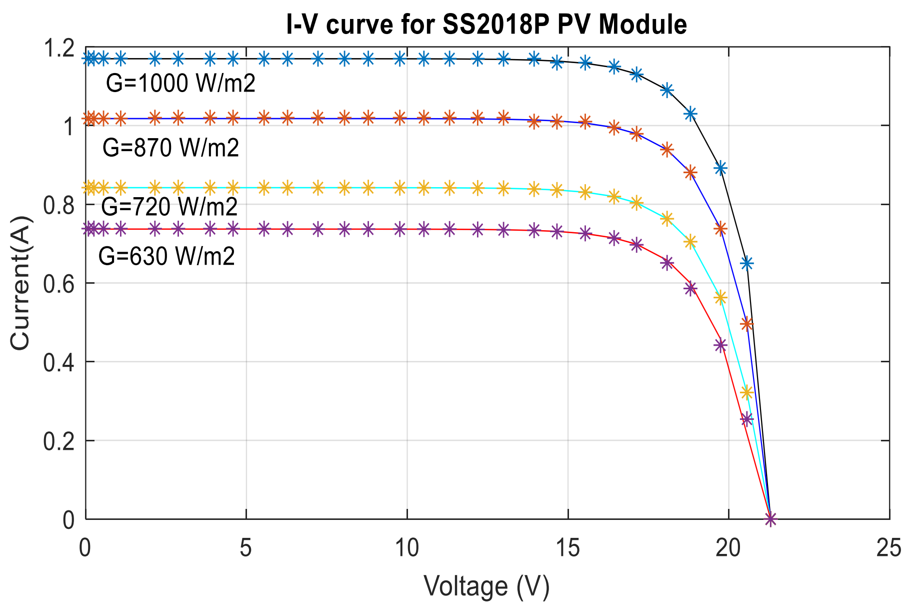
In order to further evaluate the efficiency of the proposed WOAPSO algorithm, parameters for SS2018P PV module were also estimated at different level of irradiance by utilizing the SDM model. The optimal value of five parameters (I_p, I_{sd}, a, R_s, R_{sh}) for SDM of solar PV module, at distinct levels of irradiance and constant temperature of 25° C is presented in Table 5.4, Table A6, A7, and A8 (appendix). Table 5.4 also reveals the computational time (in second) for WOAPSO is very less as compared with GSA, SCA, GWO, PSO, WOA, PSOGSA. The characteristics curve of current-voltage and power-voltage for solar PV module is redrawn based on best optimized parameters obtained by implementing the WOAPSO algorithm at a different level of irradiance i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2 and clearly depicted in Figure 5.5.

Table 5.4. Comparison of proposed WOAPSO with different parameter estimation methods for SS2018P PV module (1000 W/m^2)

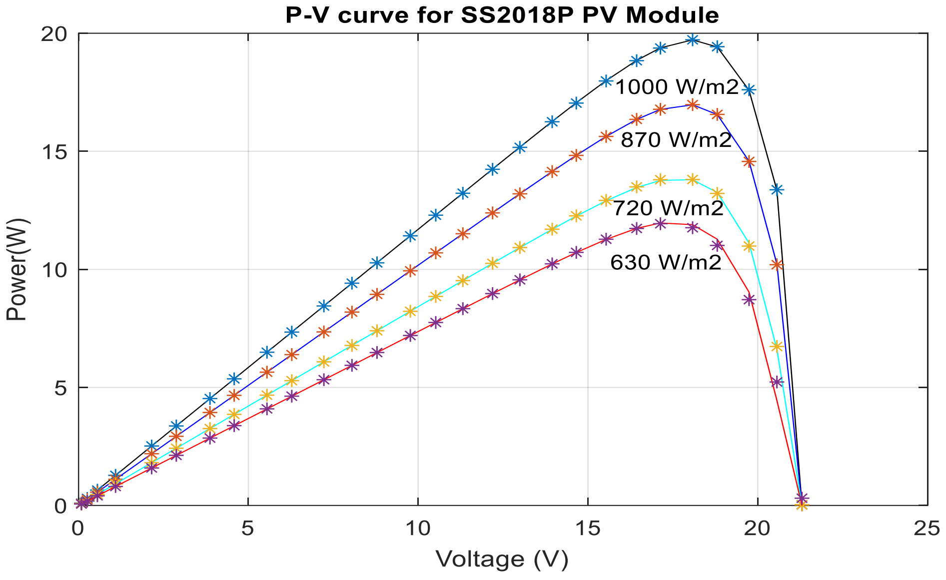
Parameters	Algorithms						
	GSA	**SCA**	**GWO**	**PSO**	**WOA**	**PSOGSA**	**WOAPSO**
Iph (A)	1.0959 ± 0.0037	1.1742 ±0.011	1 ±0.024	1.1796 ±1.009	1.181 ±0.0103	1.168 ± 0.053	1.1707 ± 0.0025
Isd (µA)	0.001 ±0.2246	0.0092 ±0.388	0.001 ±0.0759	0.001 ±0.707	0.019 ±1.034	0.001 ±1.358	0.0074 ±0.0348
Rs (Ω)	0.001 ±0.0253	0.0011 ±0.0187	0.001 ±0.0022	0.0022 ±0.583	0.0024 ±0.007	0.0075 ±0.0342	0.2 ±0.0017
Rsh (Ω)	455.5284 ± 13.67	139.676 ±19.5323	100 ± 0.842	1308.079 ±2.466	18.166 ±10.71	2000 ±4.63	177.219 ±0.026
a	53.5976	1.4147 ±1.021	1.2628 ±0.0399	1.2429 ±0.252	1.289 ±0.6784	1.246 ±0.24	1.3939 ±0.0068

	±0.2493						
RMSE	1.68E-01	1.51E-03	1.59E-01	5.13E-03	7.82E-04	3.22E-03	7.6714E-04
CPU time (s)	17	12.45	9.3	10	7.56	13.17	7.81

It can be analyzed from Figure 5.5 that the calculated data obtained by the WOAPSO is very effectively in coincidence with the experimental data set, all over the voltage range. Table A9 (attached in supplementary) represents the IAE between the calculated and experimental data sets. Every determined value of IAE (at 1000 W/m^2) in Table A9 is less than 0.0018 which indicates that the parameters optimized by the WOAPSO are very precise. The error relating the measurement results for each of 27 pair points is determined by IAE, which is calculated by using eq (5.18). The curve of IAE between experimental and estimated values at 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2, is shown in Figure 5.6.



(a)



(b)

Figure 5.5. Characteristics curve of simulated and experimental values at different level of irradiance (a) I-V curve and (b) P-V curve for SDM of SS2018P PV module

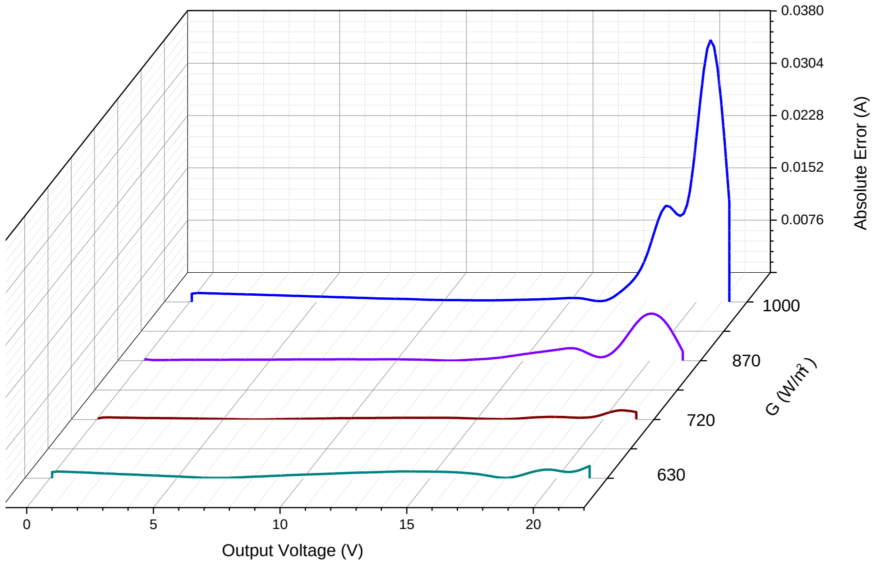
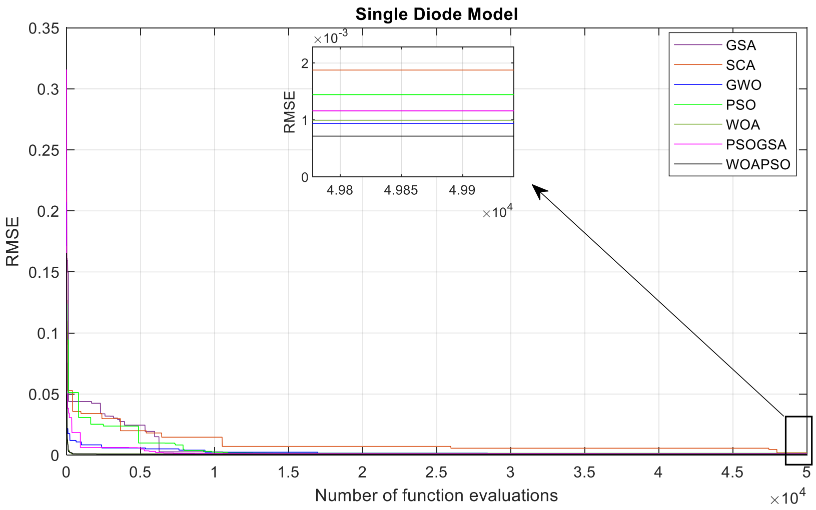


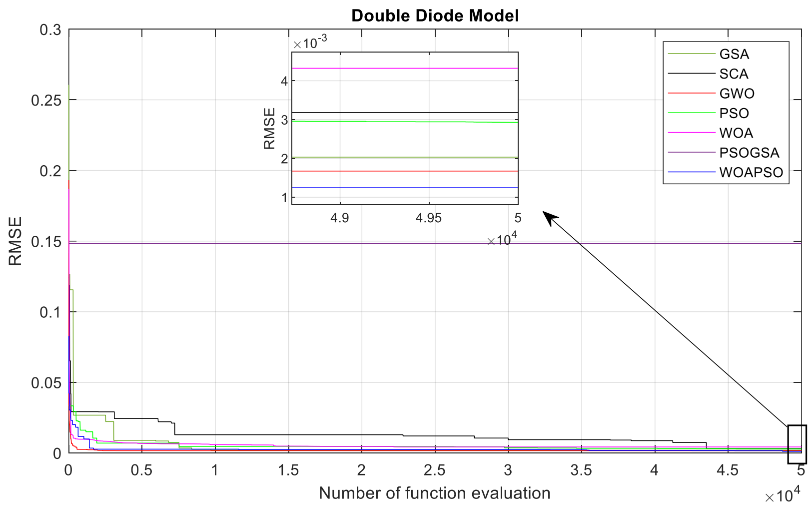
Figure 5.6. Internal absolute error between measured and simulated current for SDM of SS2018P PV module at different level of irradiance

5.4.4 Convergence analysis

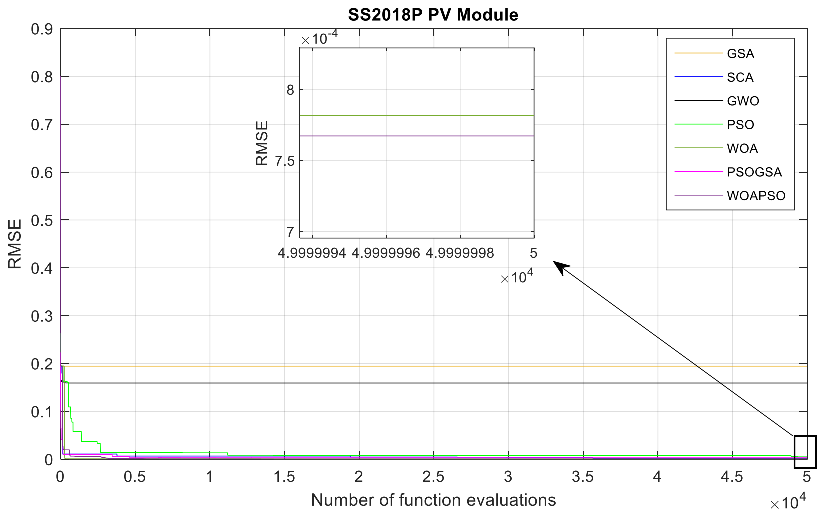
To analyze the computational competence of WOAPSO, the convergence curves of the SDM, DDM, and PV module is presented in Figure 5.7. It is depicted in Figure 5.7 that the proposed WOAPSO algorithm outperforms the GSA, SCA, GWO, PSO, WOA, PSOGSA algorithms in terms of convergence speed and generates a precise solution for the identical number of function evaluations (i.e., 50000).



(a)



(b)



(c)

Figure 5.7. Convergence curve of WOAPSO and other six algorithms for (a) SDM of R.T.C France solar cell (b) DDM of R.T.C France solar cell and (c) single diode model of SS2018P PV module

5.4.5 Robustness and statistical analysis

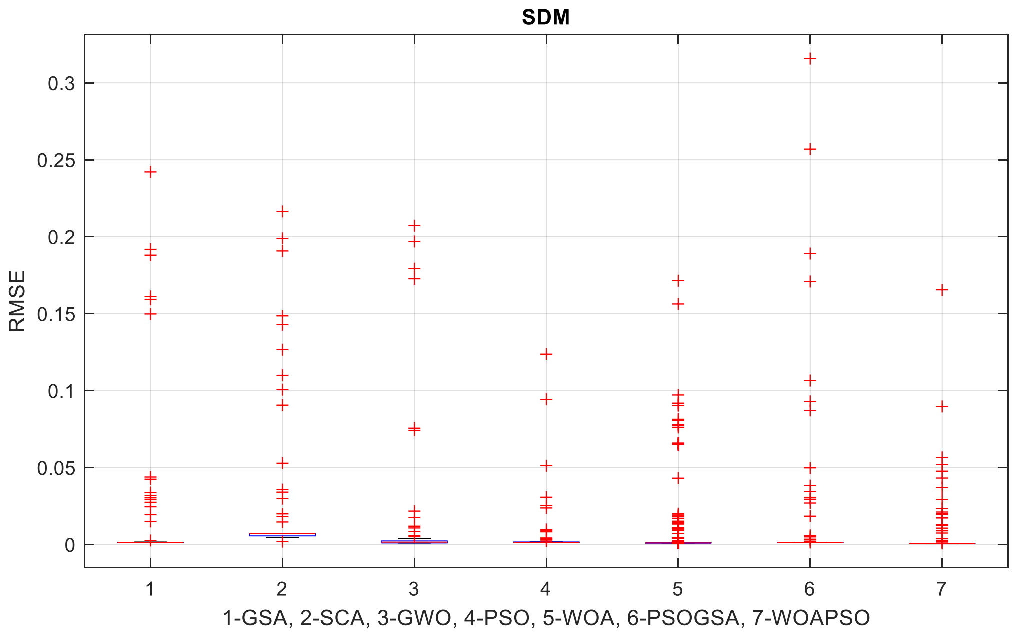
This section presents statistical evaluation based on mean, minimum, maximum, and standard deviation of RMSE for all previously implemented methods, and a comparison with respect to precision and consistency of the distinct algorithms in a total of thirty runs and depicted in Table 5.5. The mean of RMSE is calculated to evaluate the precision of algorithms and the standard deviation is calculated to evaluate the consistency of the parameter estimation methods. Furthermore, the Friedman ranking test is also performed for all algorithms and depicted in Table 5.6. From Table 5.6, it is depicted that the proposed WOAPSO algorithm significantly outperforms the GSA, SCA, GWO, PSO, WOA, PSOGSA algorithms for all three models i.e., SDM, DDM and PV module models.

The statistical results presented in Table 5.5 indicate that WOAPSO is the most accurate and reliable parameter optimization technique. As shown in Table 5.6, based on the Friedman ranking test result, the best ranking is obtained by the WOAPSO, followed by WOA, GWO, GSA, PSOGSA, SCA and PSO. Also, Figure 5.8 shows the distribution of results (i.e., RMSE) obtained from the distinct algorithms in 30 runs in the form of a boxplot graph for the SDM, DDM, and PV module. It can be clearly anticipated from Figure 5.8 that the proposed WOAPSO algorithm delivers the best results in terms of accuracy and reliability compared to the other six algorithms.

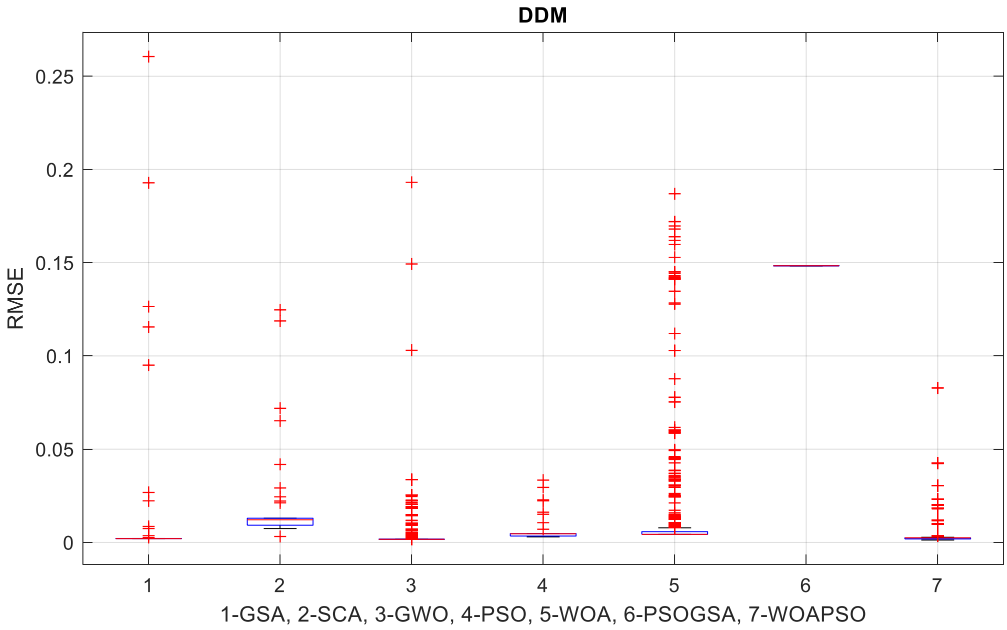
Table 5.5. Statistical results of RMSE of different algorithms for all three models

Model	Algorithm	RMSE			
		Min	Mean	Max	SD
Single diode model	GSA	1.2012E-03	5.4701E-03	2.4211E-01	1.3129E-03
	SCA	1. 9123E-03	9.6515E-03	2.1642E-01	9.4066E-03
	GWO	9. 4095E-04	1.0441E-03	1.3506E-03	1.4050E-05
	PSO	1. 4320E-03	1.2534E-03	1.4074E-03	1.1520E-04
	WOA	9. 9529E-04	9.2032E-04	7.1240E-03	9.0250E-03
	PSOGSA	1.2400E-03	1.7660E-03	5.2460E-03	1.9880E-03
	WOAPSO	**7.1701E-04**	**7.8030E-04**	**1.3436E-03**	**2.4290E-06**
Double diode model	GSA	2.0330E-03	4.7041E-03	2.6058E-01	1.5796E-03
	SCA	3.1800E-03	1.7932E-03	1.2470E-01	7.7256E-02
	GWO	1.6000E-03	2.6901E-03	8.2830E-02	2.6995E-03
	PSO	2.9000E-03	4.9713E-03	3.3402E-02	3.5833E-02
	WOA	4.3000E-03	5.2967E-03	1.8698E-02	3.9481E-03
	PSOGSA	1.4812E-01	1.4833E-01	1.4732E-01	1.0977E-02
	WOAPSO	**9.8412E-04**	**1.2481E-03**	**1.9312E-03**	**1.0581E-03**
SS2018P module model	GSA	1.6877E-01	1.9462E-01	2.0011E-01	4.4500E-03
	SCA	1.5149E-03	5.2657E-03	2.0345E-01	1.0058E-02

GWO	1.5938E-01	1.5940E-01	5.2494E-01	1.6793E-02
PSO	5.1329E-02	1.2512E-02	2.6323E-01	1.9334E-02
WOA	7.8164E-04	1.8268E-03	2.1078E-02	1.3639E-03
PSOGSA	3.2258E-03	3.9510E-03	2.2333E-01	4.0336E-03
WOAPSO	**7.6714E-04**	**7.4601E-04**	**7.5388E-04**	**7.4516E-05**



(a)



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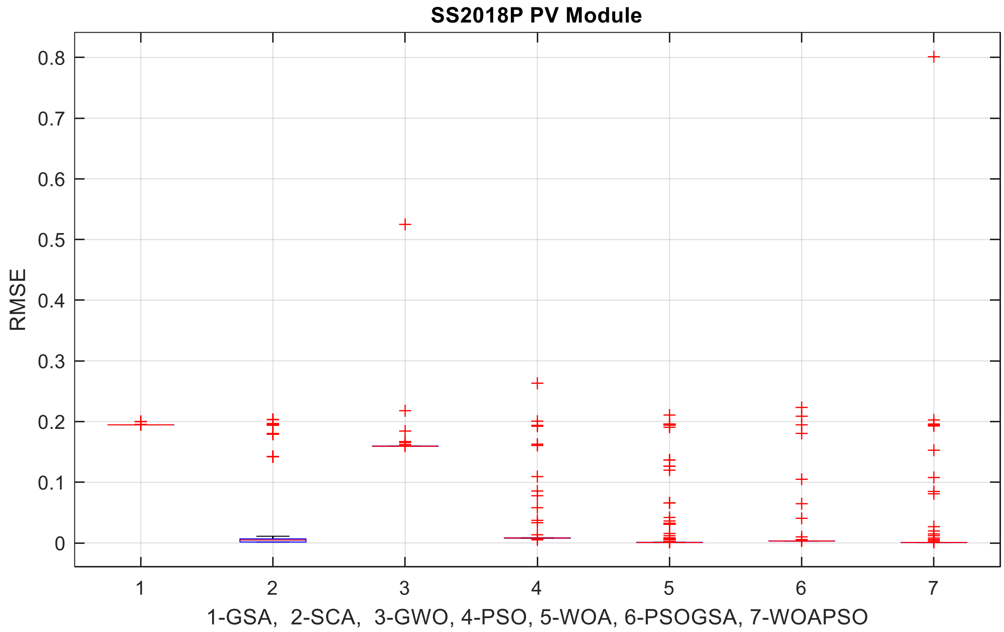


(c)

Figure 5.8. Boxplot graph of best RMSE in 30 runs for (a) SDM (b) DDM (c) Polycrystalline SS2018P PV module

Table 5.6. Ranking of the proposed WOAPSO and other compared algorithm on three PV models according to the Friedman test

Algorithms	Friedman ranking	Final ranking
GSA	3.9	4
SCA	5.91	6
GWO	3.36	3
PSO	6.53	7
WOA	2.05	2
PSOGSA	5.22	5
WOAPSO	1	1

5.4.6 CPU time

Within this section, the execution average time of each algorithm on the three PV models is calculated and illustrated in Figure 5.9. WOAPSO requires very less time of about 26.1 s as compared to GWO, PSO, SCA, WOA and PSOGSA, while GSA has the worst execution time of approximately 52 s.

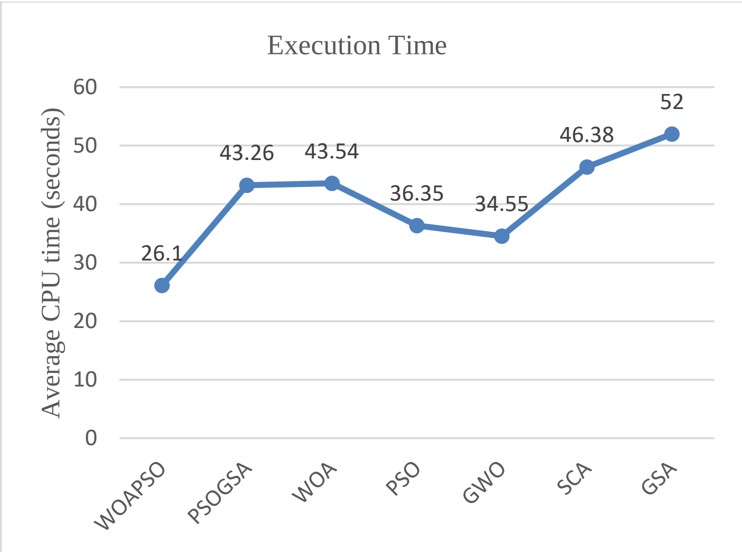


Figure 5.9. Comparison of the execution time

5.5 Conclusion

In this chapter hybridization of whale optimization and particle swarm optimization algorithm (WOAPSO) is anticipated where only the exploitation ability of PSO is implemented in pipeline mode when WOA stops to improve the best-found solution. The collaboration of both metaheuristic algorithms is able to establish an effective balance between exploitation and exploration search ability. The proposed technique is further used for parameter estimation of three PV cell models i.e., SDM, DDM, and SS108P PV panel module model at different operating conditions. It should be noted that this suggested technique is, for the first time, intended to reliably track the estimation of parameters for PV. The observations based on the experimental findings are defined as follows:

- The proposed WOAPSO is relatively accurate and reliable at delivering the solution in terms of RMSE as compared with other algorithms such as GSA, SCA, GWO, PSO, WOA, PSOGSA, and existing algorithms in the literature.
- The I-V and P-V characteristic curves and IAE results indicate that WOAPSO can generate the optimized value of estimated parameters for all the models of solar PV cell as compared with other algorithms.
- The statistical analysis clearly depicts the robustness of the proposed WOAPSO technique on parameter estimation problem at different operating conditions.
- The convergence curves demonstrate that the best values of estimated parameters are obtained by WOAPSO, and RMSE is 7.1700E-04 and 9.8412E-04 in the case of single and double diode respectively.
- At different irradiation levels (i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2), the proposed WOAPSO algorithm is best in producing optimized parameters (I_p, I_{sd}, a, R_s, R_{sh}) and minimum value of RMSE for PV module even at a low level of irradiation (630 W/m^2).

From the above discussion, it can be concluded that WOAPSO is an efficient and robust technique to estimate the unknown optimized parameters of the solar PV model at different operating conditions. For future study, the implementation of proposed WOAPSO to solve the other problems related to energy optimization such as economic load dispatch, energy scheduling and optimization of PV array configuration may also be interesting for scientists and research community.

CHAPTER-6

IMPLEMENTATION OF PROPOSED OTSA ALGORITHM FOR PARAMETER ESTIMATION OF SOLAR CELL/MODULE

6.1 Introduction

In recent days, the availability of clean and sustainable energy is an important technical and scientific challenge for human society. These challenges spark the interest to develop renewable energy sources, e.g., solar, wind, geothermal, tidal, hydro energy, etc. [99]. Solar energy is an increasingly trendy way to supplement energy usage as it is the clean, amplest, and freely accessible energy source [100]. Thus, the global solar electricity market is rapidly growing and is projected to reach $194 billion by 2027 [101]. The PV systems are employed to convert solar energy into electric energy. The importance of PV systems is estimated as a major stimulating topic by scientists/researchers and companies to progress their energy adaption and reduce the price [102]. Furthermore, the production firms require assurance of the maximum power production from PV power plants.

It is well known fact that the energy generation from PV power systems strongly depends on weather conditions, solar irradiance, and temperature [103-105]. Besides, these systems unavoidably undergo degradation along with the possible occurrence of electrical faults [106]. The effective modeling of the PV cells is needed to control and predict the performance of the solar systems at different working conditions. However, the modeling and parameter assessment of PV cells is a crucial task. The nonlinear dimensions and sporadic of meteorologic static make cell constraints difficult to identify [107]. Several models were developed based on the physical process and associated variables of PV cells. For example, single-diode, double-diode, and triple-diode models have successfully represented the PV systems' behavior SDM is majorly used to approximate equivalent circuit parameters because of ease and acceptance. The DDM is highly accurate for lower solar irradiance than SDM, but it consumes a longer time. The assessment of equivalent circuit parameters helps to determine the accuracy and dependability of the models. However, the model parameters are not accessible due to unbalanced operational cases like faults and aging. Therefore, the development of an active methodology to accurately extract these parameters turn out to be critical. The evolutionary algorithms were proposed to achieve more accurate and precise parameters from nonlinear implicit equations [108]. The bio-related algorithms are more accurate and powerful optimization algorithms to simplify nonlinear transcendental equations, as it does not include complex mathematics.

Previously, several algorithms have been utilized to enhance the parameter estimation accuracy for PV systems. These algorithms can be divided into two groups, deterministic and metaheuristic [109]. Both groups of algorithms have merits and demerits depending on the function. Deterministic algorithms include least squares [110], Lambert W-functions [111] , and the iterative curve fitting methods. These algorithms impose several model restrictions as they are sensitive to the initial solution and generally converge at local optima. Metaheuristic methods are represented by PSO [18], chaos particle swarm optimization (CPSO) [112], harmony search (HS) [113], CS [71], ABC [114], CSO [31], modified generalized opposition based teaching learning based optimization (GOTLBO) [91], DE [85], improved adaptive differential evolution (IADE) [115], GA [90], SA [68], biogeography based optimization algorithm with mutation strategies (BBO-M) [29], Nelder-mead modified particle swarm optimization (NM-MPSO) [116], and PS [69].

In very recent work, Kaur *et al.* proposed a bio-inspired metaheuristic optimization algorithm named TSA [117]. It is demonstrated that the TSA can solve real case studies having unknown search spaces. It is also proposed that the TSA generates better optimal solutions than that of other competitive algorithms. However, the TSA endures from some limitations such as being slow to converge, being trapped at local optima, and requiring large computational time. These limitations are because certain solutions are modified toward the best solution, while some solutions are not updated toward the best solution. It is possible to overcome these limitations by considering the opposite direction. The opposition-based learning (OBL) mechanism has received the most attention recently and used to increase the efficiency of metaheuristic algorithms. It has an interesting property that it can search in the reverse direction to the current solution, and this led to metaheuristic algorithms being searched throughout the search space. The OBL-based technique can be integrated with the basic version of TSA for managing a good trade-off between exploration and exploitation.

In this chapter, an opposition-based TSA (OTSA) is proposed. The OBL technique features are combined with the TSA algorithm to provide a good trade-off between exploration and exploitation capabilities. The proposed algorithm is employed on three distinct PV modules at different irradiance and temperature levels. The statistical analysis is performed to check the effectiveness of the anticipated algorithm. In section 6.4, the OTSA simulation results are discussed and compared with pre-existing metaheuristic algorithms. According to the literature survey presented in Table 6.1, OTSA has not been implemented yet for the parameter extraction of the solar cell (and it cannot be used to establish a PV parameter estimation technique that can overcome all existing techniques).

Table 6.1. Comprehensive review of application of metaheuristic algorithms for parameter extraction of PV models

Model	Parameters Extracted	Technique	Reference	Description
Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Genetic Algorithm	[90]	Small deviation in the value of optimized parameters.
Single Diode	I_p, I_{sd}, a_1, R_s, R_{sh}		[118]	Reverse saturation current was highly accurate with slow extraction process.
Single Diode	I_{sd}, I_p, R_s, R_{sh}, a_1		[119]	Problem of local minima is found in non-convex cases.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}		[67]	Accurate optimized parameters are obtained for a wide

				range of radiation and temperature.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Particle Swarm Optimization	[120]	Accuracy and computational time of PSO technique is superior to GA.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}		[121]	The extracted parameters were further investigated to identify the various mechanisms affecting the cell performance.
Single Diode	a_1, R_s, R_{sh}		[122]	PSO technique produced precise PV cell parameters under varying radiation and temperature.
Single Diode	I_p, I_{sd}, a_1, R_{sh}, R_s		[89]	Improved overall searching capability under multiple local maxima.
Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}		[8]	Extracted parameters gives a practical representation of the PV system.
Single Diode	a_1, R_s, R_{sh}		[76]	Proposed method eliminates the assumption in the ideality factor.
Single Diode	a_1, I_{sd}, R_s, R_{sh}, δ_s, Φ_{sh}		[123]	Proposed technique has a high speed of convergence and easy to implement.
			[124]	Proposed two DE methods: boundary based, and penalty

Double Diode	I_p, I_{sd1}, I_{sd2}, R_s, R_{sh}, a_1, a_2	Differential Evolution Algorithm		based to extract the parameters of PV module with a smaller number of control parameters.
Single Diode	a_1, R_s, R_{sh}		[125]	Proposed a DE technique with improved ability to determine the parameters under different radiation and temperature.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}		[85]	Proposed method has improved convergence speed.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Simulated Annealing	[68]	Proposed method solves transcendental function of the I-V curve.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Pattern Search	[69]	Proposed method has higher accuracy as compared to other optimization methods.
Single Diode	a_1, R_s, R_{sh}	Bacteria Foraging Algorithm	[126]	Proposed a new objective function by taking the derivative of the basic current equation of single diode model.
Improved Single Diode	I_p, I_{sd}, a_1, R_{sh}, R_s, E_g	Cuckoo Search	[71]	The proposed method has the lowest root mean squared error value.
			[70]	Harmony search variants are proposed.

Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Harmony Search		The first variant finds the best harmonies in the harmony memory and the second helps in improving the probability of generating a harmony.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Artificial Bee Swarm Optimization	[73]	The proposed method is superior as compared to other optimization methods as it has the lowest root mean square error.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	Bird Mating Optimizer	[72]	The proposed method was able to avoid premature convergence.
Single Diode	I_{sd}, I_p, R_s, R_{sh}, a_1		[127]	Can easily estimate the PV parameters with smaller number of control parameters.

6.2 Problem Formulation

In a photovoltaic solar cell, the parallel circuits are formulated using SDM and DDM. Therefore, the correlation between current and voltage is represented using equivalent circuit models.

6.2.1 Photovoltaic panel module model

The output terminal for the PV panel module is the relationship between current and voltage, which is expressed in equation 6.1 and in Figure 6.1, the equivalent circuit of the PV module, can be clearly described.

$$I_l/N_p = I_p - I_{SD}\left[exp\left(\frac{q\left(V_l/N_s + R_sI_l/N_p\right)}{a_1k_BT}\right) - 1\right] - \frac{V_l/N_s + R_sI_l/N_p}{R_{sh}} \tag{6.1}$$

where N_s and N_p represent the number of solar cells connected in series and parallel, respectively. It is depicted in figure 1 that only five parameters (I_p, I_{SD}, a, R_s and R_{sh}) are needed to estimate for the minimum value of RMSE, summation of absolute error (SAE) and mean absolute error (MAE).

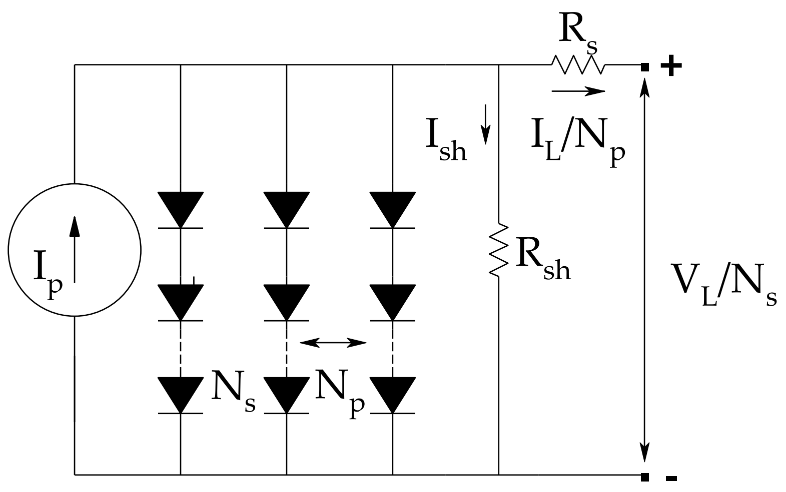


Figure 6.1. Model of Photovoltaic Panel module having equivalent circuit

6.2.2 Objective function

In this work, the key deliverables are the optimization of unknown specification for SDM to reduce the error between experimental and estimated data. During optimization, unknown parameters ($I_p, I_{SD}, a, R_s, R_{sh}$) are used as a decision variable, while the cumulative squared error between simulated and measured data is used as an objective function. Furthermore, the proposed algorithm is validated by calculating the SAE and MAE. The objective function for error used here is the same as the authors have used previously in [3], [4] as:

$$RMSE = \sqrt{\frac{1}{k}\sum_{N=1}^{k} f(V_l, I_l, \mathrm{X})^2} \tag{6.2}$$

$$SAE = \sum_{N=1}^{k} |I_{measured} - I_{calculated}| \tag{6.3}$$

$$MAE = \frac{1}{k}\sum_{N=1}^{k} |I_{measured} - I_{calculated}| \tag{6.4}$$

where V_l and I_l are the measured voltage and current of the PV module. The parameter 'k' stands for the number of experimental data set. The best solution found by TSA is represented by a vector X. For the PV panel module model,

$$\begin{cases} \mathrm{f_{module}}(\mathrm{V_l}, \mathrm{I_l}, \mathrm{X}) = \mathrm{I_p} - \mathrm{I_{SD}}\left[\exp\left(\frac{\mathrm{q}\left(\frac{\mathrm{V_l}}{\mathrm{N_s}} + \frac{\mathrm{R_s I_l}}{\mathrm{N_p}}\right)}{\mathrm{a_1 k_B T}}\right) - 1\right] \\ \qquad - \frac{\mathrm{V_l/N_s + R_s I_l/N_p}}{\mathrm{R_{sh}}} - \mathrm{I_l/N_p} \\ \qquad (\mathrm{X} = \mathrm{I_p}, \mathrm{I_{SD}}, \mathrm{a_1}, \mathrm{R_s}, \mathrm{R_{sh}}) \end{cases} \tag{6.5}$$

6.3 OTSA algorithm

6.3.1 Tunicate Swarm Algorithm

The TSA is a bio-inspired based metaheuristic algorithm for global optimization [6]. Tunicates can be noticed over many meters away as bright bio-luminescent and produce a pale blue-green light. Tunicates are shaped in one end closed cylinder and have a size of few millimeters. The presence of gelatinous tunic in each tunicate helps to combine all individual tunicates. Nevertheless, every individual tunicate takes water from the surrounding and thrusts as jet propulsion through open end atrial siphons. The jet propulsion actions of tunicates can be understood using the mathematical model and the following conditions: prevent collisions between candidate solutions, step more toward the location of the best solution, and stick close to the best solution.

(A) Prevent collisions between candidate solutions

Initialize the parameters $\vec{A}$ (constant), gravity force ($\vec{G}$), water flow advection in the deep ocean ($\vec{F}$), social force $\vec{M}$ and the maximum number of iterations:

$$\vec{A} = \frac{\vec{G}}{\vec{M}} \tag{6.6}$$

$$\vec{G} = c_2 + c_3 - \vec{F} \tag{6.7}$$

$$\vec{F} = 2 * c_1 \tag{6.8}$$

$$M = \lfloor P_{min} + c_1 * P_{max} - P_{min} \rfloor \tag{6.9}$$

where, c_1, c_2, c_3 are random number in the range [0, 1], P_{min} and P_{max} are considered as 1 and 4.

(B) Step more toward the location of the best solution

The search agents are moved in the direction of the finest neighbors after successfully preventing a conflict with neighbors:

$$\overrightarrow{PD} = \left|\overrightarrow{FS} - rand * \vec{P}_p(x)\right| \tag{6.10}$$

where, $\overrightarrow{PD}$ is the total distance between the search agent and food source, $rand$ is the random number in the range [0, 1], x indicates the current iteration, $\overrightarrow{FS}$ indicates the position of the food source, $\vec{P}_p(x)$ is the position of tunicates.

(C) Stick close to the best solution

The search agent could even establish its position as the leading search agent.

$$\vec{P}_p(x) = \begin{cases} \overrightarrow{FS} + \vec{A} * \overrightarrow{PD}, if\ rand \geq 0.5 \\ \overrightarrow{FS} - \vec{A} * \overrightarrow{PD}, if\ rand\ < 0.5 \end{cases} \tag{6.11}$$

The position of all the tunicates is updated with respect to the position of the first two tunicates as follows:

$$\vec{P}_p(x+1) = \frac{\vec{P}_p(x) + \vec{P}_p(x+1)}{2 + c_1} \tag{6.12}$$

where, $\vec{P}_p(x+1)$ represents the updated position of tunicates.

6.3.2 Opposition Based Learning Method

The OBL method was first developed in 2005 [128]. This approach has been further introduced in [129, 130] and shown to be a successful method of making the search patterns of metaheuristics more real. This approach stems from the simultaneous estimate of the opposite pairs of the base agents to improve the likelihood of meeting a matching agent. The contrary of a real number $N \in [j_L,\ j_U]$ can be provided by $\vec{N}$ as follows:

$$\vec{N} = j_L + j_U - N \tag{6.13}$$

where j_L and j_U are known as lower and upper bound of a real number. While in multi-dimensional space, N can be expressed as $N_k = \{N_{k1}, N_{k2}, N_{k3}, \dots \dots, N_{kt}\}$ and $N_{kt} \in [j_{Lt},\ j_{Ut}]$, where $t = 1,2,3,4, \dots \dots, n$ and the corresponding opposite points are as follows:

$$\begin{aligned} \overline{N} &= \{\overline{N}_{k1,}, \overline{N}_{k2}, \overline{N}_{k3}, \dots \overline{N}_{kt}\} \\ \overline{N}_{kt} &= j_{Lt} + j_{Ut} - N_{kt} \end{aligned} \tag{6.14}$$

During the optimization process, opposite points $\overline{N}$ are replaced by the corresponding solution N based on best fitness value. In other words, the position of the population is updated on the basis of finest values of $\overline{N}$ and N. Figure 6.2 illustrates the complete process of opposition based learning mechanism.

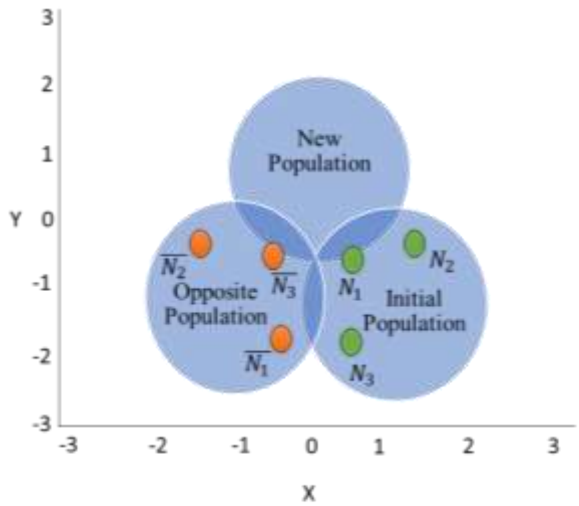


Figure 6.2. Illustration of opposition based learning mechanism

6.3.3 Proposed Algorithm

This section describes the proposed opposition-based TSA (OTSA) algorithm. The OBL mechanism is employed to enhance the performance of traditional TSA. The OTSA can also integrate the search capabilities of the classic TSA with OBL to maximize the exploration of solution space. The integration of OBL does not influence the basic functionality of TSA, and the precision of the optimal solution is enhanced. In this manner, OTSA can limit the number of the initial population, which improves the convergence to the optimal solution since it's exploring the solution space for an optimization problem.

Let us consider that a problem requires a population of 200 initial solutions. The OTSA can initialize 100 solutions in the specified order and compute their respective opposite solutions by utilizing the OBL principle. Only the top 100 solutions are identified in an iterative process before ranking them. However, the population setting in OTSA may also influence the occurrence of call functions needed throughout the optimization procedure. The computational effort generally depends on the implementation and evaluation of an optimization problem. This fact directly corresponds to the NFL theorem [131], which specifies that the algorithms cannot be enhanced without any cost. However, the NFL has also noted that some algorithms are not suitable for solving all types of optimization problems. This is the primary motivation for the development of the proposed OTSA.

The proposed methodology enhances the basic version of TSA via two phases. In the first phase, the OBL mechanism is implemented to initialize the population to reduce the convergence rate and avoids the optimal local solution by searching for solutions in the entire search domain. In the second step, the population solution is updated, and the OBL mechanism is also used to check whether the opposite direction update is better than the existing update.

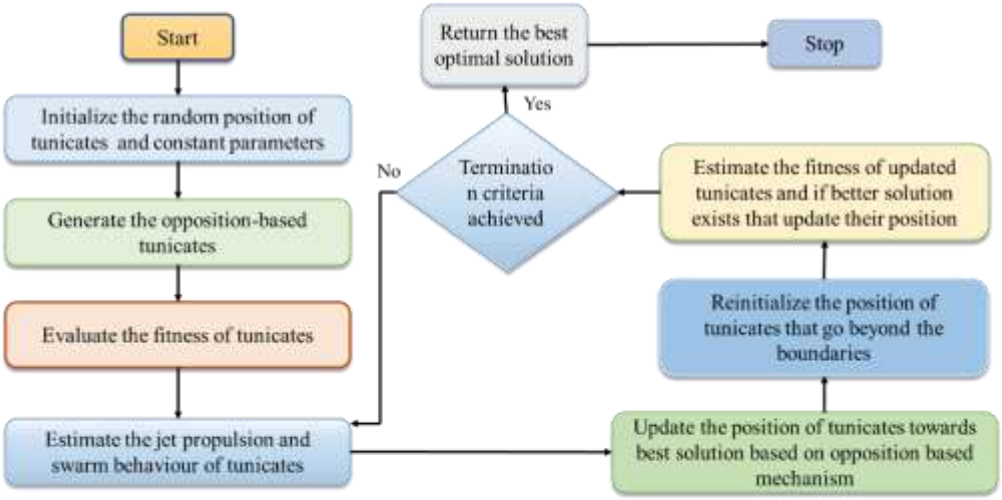


Figure 6.3. Process flow diagram of proposed OTSA

6.4 Results and Discussion

6.4.1 Experimental setup and results

The proposed OTSA algorithm is validated by estimating the unknown parameters of SDM for three different PV modules under variable weather conditions. Figure 6.4 demonstrates the experimental setup for the measurement of PV modules' characteristics. First PV module consists of 36 serially connected solar cells (Solarex MSX 60 polycrystalline solar panel). This module is irradiated at different irradiance levels (500 W/m^2, 750 W/m^2 and 1000 W/m^2) at a constant temperature of 25 °C. Second PV module comprises 36 serially connected polycrystalline cells (SS2018P PV module). The I-V characteristics are measured at different irradiance levels (720 W/m^2, 870 W/m^2, and 1000 W/m^2) at a constant temperature of 25 °C. The data collection involves a total of 20 I-V measurements for solar cells and 27 for PV modules. The current and voltage for the solar PV module (SS2018P) are determined at variable resistive load (0.1–250 Ω, 2 A). Another PV module consists of 20 serially connected monocrystalline cells (Leibold Solar Module LSM 20). This module is irradiated at the temperature of 24°C under an irradiance level of 360 W/m^2 [103]. The measured values of current and voltage for all three PV modules are shown in Tables A1, A10 (appendix).

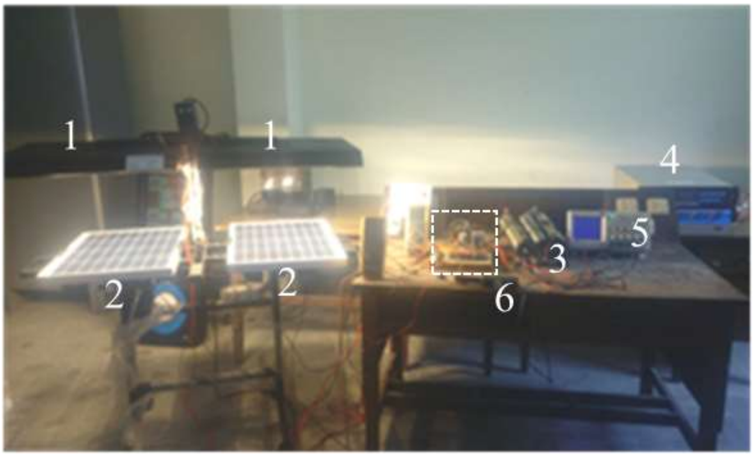


Figure 6.4. Experimental setup for measurements of SS2018 and Solarex MSX-60 PV modules (1: Halogen lamps, 2: PV modules, 3: Resistive load 4: PV array simulator, 5: Oscilloscope, 6: Boost converter and microcontroller)

6.4.2 Parameter extraction by OTSA algorithm

The proposed OTSA algorithm is implemented on the MATLAB 2018a platform with Intel ® core ™ i7-HQ CPU, 2.4 GHz, 16 GB RAM Laptop. To organize the experiment, the number of populations and the anticipated number of objective function evaluations are set at 30 and 50,000, respectively. Furthermore, a minimum of 30 distinct runs is conducted out to avert the contingency. The upper and lower bound limits for each parameter are tabulated in Table 6.2 for a rational evaluation.

Table 6.2. Range of parameters for PV Module

Parameter	Lower Bound	Upper Bound
I_p (A)	0	10
I_{sd} (µA)	0	50
R_s (Ω)	0.001	2
R_{sh} (Ω)	0	2000
a	0	100

6.4.2.1 Parameter extraction of Solarex MSX 60 module

For Solarex MSX 60 PV Module, the proposed algorithm is employed to extract parameters (I_p, I_{sd}, a, R_s, R_{sh}) of SDM. The parameters are also extracted using different algorithms for comparison. Table 6.3 signifies the optimized parameters, RMSE, SAE, and MAE values for irradiance level of 1000 W/m^2. The parameters and error magnitudes for other irradiance levels (500 W/m^2, and 750 W/m^2) are shown in Tables A11 and A12 (appendix). It is found that the proposed OTSA algorithm generates the lowest RMSE, SAE, and MAE values of 2.057E-04, 5.77E-08, and 2.52E-09, respectively. The RMSE, SAE, and MAE values of the OTSA algorithm are smaller than the performance of the WOA [22], GWO [37], SCA [132], ALO [133], PSOGSA [134], TSA algorithms as well pre-existing algorithms. Here RMSE, SAE, and MAE values are acquired as the index for assessing the performance of algorithms. Figures 6.5 (a & b) represent the simulated and measured current-voltage (I-V) and power-voltage (P-V) curves for different irradiance levels. The simulated data consists of the best-optimized parameters obtained by the OTSA algorithm. The measured data shows good agreement with the calculated one. The curves of IAE between experimental and simulated current for SDM at different irradiance levels are shown in Figure 6.6.

Table 6.3. Comparison of proposed OTSA with different parameter estimation methods for Solarex MSX-60 PV module (1000 W/m^2, 25 °C)

Algorithms	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	SAE	MAE
NM [107]	3.8084	0.0005	0.3692	169.047	1.0003	9.613E-02	NA	NA
BC [135]	3.8080	0.0012	0.3160	146.080	1.0450	4.202E-02	NA	NA
SFLA [106]	3.80	0.2308	0.18	340.001	1.316	1.68E-01	NA	NA
ER-WCA [111]	3.812	1.399	0.2235	914.689	1.3325	1697E-02	NA	NA
WOA	1.131	0.6535	0.008	41.939	81.61	1.230E-03	1.41E-04	6.37E-05

GWO	3.39	0.293	0.001	180.89	56.50	8.129E-02	1.79E-03	3.14E-03
SCA	3.7705	0.0027	0.009	53.07	1.205	6.14E-02	1.06E-04	6.40E-04
ALO	3.368	0.145	0.03	4.66	65.83	9.703E-02	1.41E-03	4.09E-03
PSOGSA	0.7643	0.501	0.001	89.03	1.53	1.604E-03	1.10E-04	6.41E-03
TSA	3.395	1.775	0.237	894.82	93.87	8.774E-03	1.24E-03	4.21E-03
OTSA	3.3743	0.269	0.0003	1934.042	1.735	**2.057E-04**	**5.77E-08**	**2.52E-09**

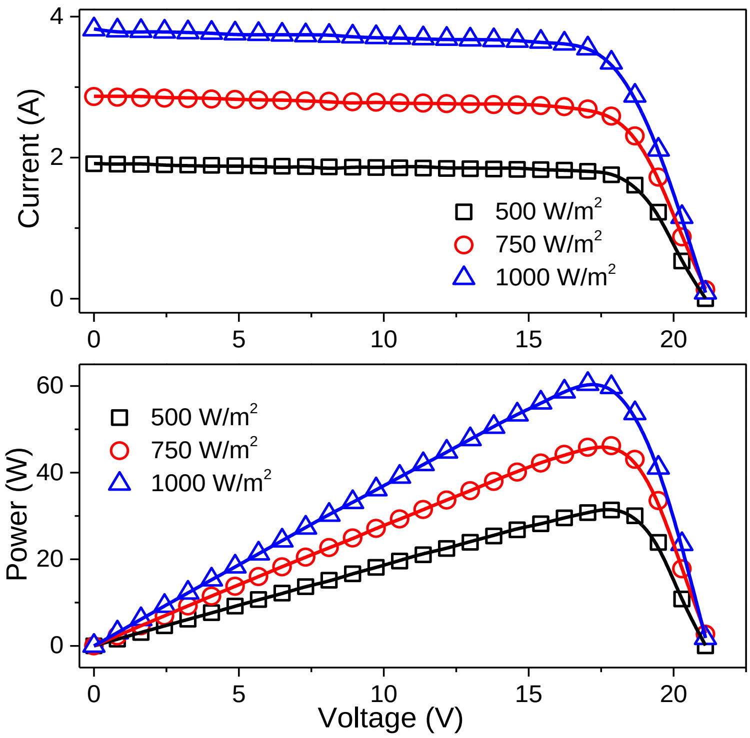


Figure 6.5. The I-V and P-V curves for the SDM of SolarexMSX 60 PV module at different irradiance levels. Measured data is represented by symbols, and optimized data is represented by solid lines

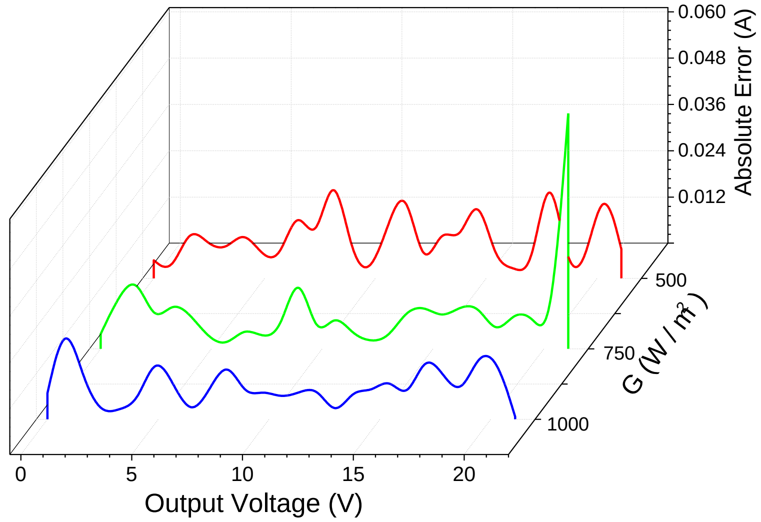


Figure 6.6. Internal absolute error between measured and simulated current for SDM of SolarexMSX 60 PV module at different irradiance levels

6.4.2.2 Parameter extraction of SS2018P module

The efficiency of the proposed OTSA algorithm is further evaluated by another PV module (SS2018P PV). The parameters were estimated at different levels of irradiance by utilizing the SDM model. The optimized parameters, RMSE, SAE, and MAE values for irradiance level of 1000 W/m^2 are charted in Table 6.4. The parameters and error magnitudes for other irradiance levels (720 W/m^2, and 820 W/m^2) are shown in Tables A13 and A14 (appendix). It is noticed that the proposed OTSA algorithm generates the lowest RMSE, SAE, and MAE values as compared to pre-existing algorithms. The characteristics curve of current-voltage and power-voltage for solar PV module is redrawn based on best-optimized parameters obtained by implementing the OTSA algorithm at different irradiance levels (1000 W/m^2, 820 W/m^2, and 720 W/m^2) is depicted in Figure 6.7. It is found that the calculated data obtained by the OTSA is very effective in keeping with the experimental data set. The curves of IAE between experimental and simulated current for SDM at different irradiance levels are shown in Figure 6.8.

Table 6.4. Comparison of proposed OTSA with different parameter estimation methods for SS2018 PV module (1000 W/m^2)

Algorithms	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	SAE	MAE

WOA	1.099	7.79	0.172	1654.52	71.99	1.15E-03	4.62E-04	3.79E-03
GWO	1.092	2.08	0.257	661.6292	100	1.89E-03	1.78E-04	1.13E-04
SCA	1.102	0.01	0.558	354.70	40.11	2.18E-03	4.16E-03	1.70E-03
ALO	1.41	0.09	0.003	901.45	1.8	1.45E-03	4.41E-04	2.57E-04
PSOGSA	1.118	0.432	1.795	937.691	25.969	1.92E-02	7.41E-03	2.63E-04
TSA	1.099	5.60	0.9107	884	19.2463	9.73E-04	8.14E-04	2.05E-06
OTSA	1.172	0.0731	0.0001	129.21	1.3	**6.83E-04**	**2.62E-06**	**4.99E-05**

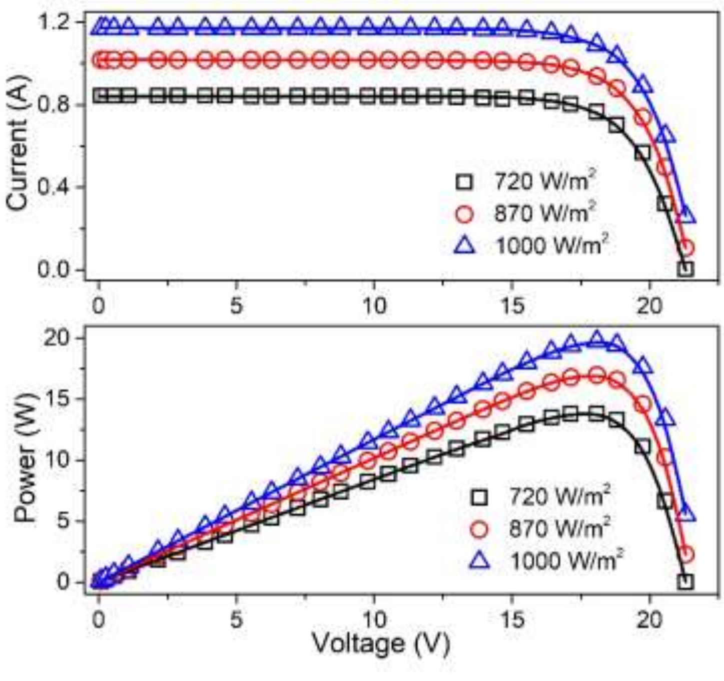


Figure 6.7. Characteristics I-V and P-V curves of simulated and experimental values at different irradiances for SDM of SS2018P PV module. Symbols represent the measured data, while the solid lines represent the simulated data

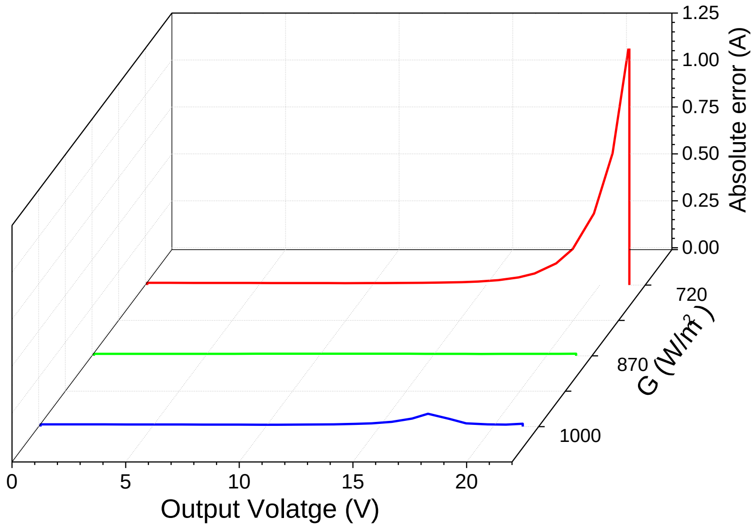


Figure 6.8. Internal absolute error between measured and simulated current for SDM of SS2018P PV module at different irradiance levels

6.4.2.3 Parameter extraction of LSM 20 module

The proposed OTSA algorithm is also employed to analyze the monocrystalline LSM20 PV module. The parameters of SDM were estimated at an irradiance level of 360 W/m^2. Table 6.5 summarizes the optimized parameters, RMSE, SAE, and MAE values. Interestingly, the OTSA algorithm shows good performance for the monocrystalline PV module. These findings validate the applicability of OTSA for different types of PV cells. The error values (RMSE, SAE, and MAE) of the OTSA algorithm are smaller than that of WOA, GWO, SCA, ALO, PSOGSA, TSA, and pre-existing algorithms. The lowest RMSE, SAE, and MAE values are 4.48E-06, 1.69E-04, and 8.25E-06, respectively. A smaller magnitude of the IAE demonstrates the accuracy of optimized parameters produced by the OTSA algorithm. Figure 6.9 displays the measured and simulated I-V and P-V characteristic curves. The simulated curves are based on the best-optimized parameters obtained by the OTSA algorithm. It can be observed that estimated parameters show good agreement with the measured one, which proves the efficient performance of the OTSA.

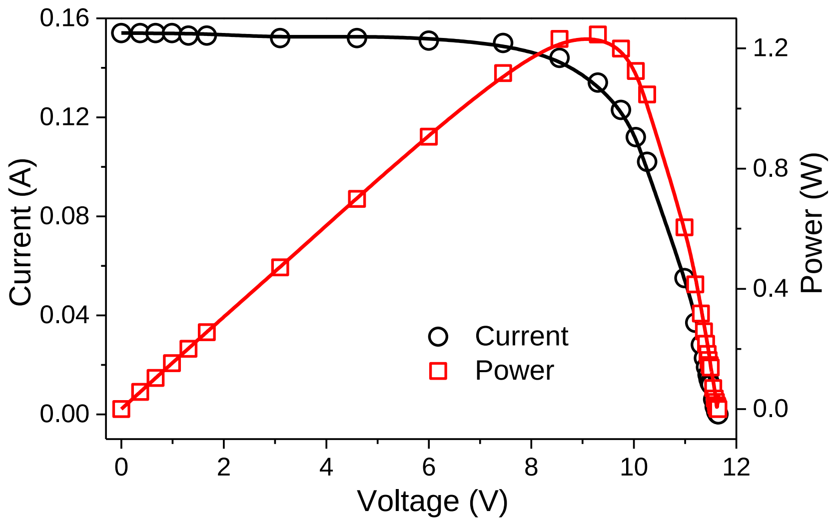


Figure 6.9. I-V and P-V curves for monocrystalline Leibold solar module (LSM 20). Open symbols represent the measured data, and solid lines show estimated data

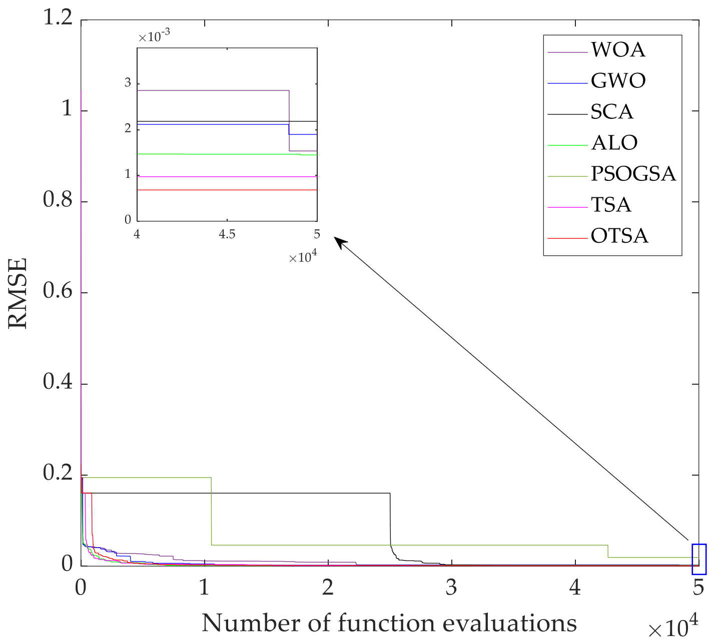
Table 6.5. Estimated parameters of Leibold solar module (LSM 20) using different algorithms

Algorithms	**I_{ph} (A)**	**I_{sd} (μA)**	**R_s (Ω)**	**R_{sh} (Ω)**	**a**	**RMSE**	**SAE**	**MAE**
TGA [136]	0.1549	0.0016	0.280	160.60	1.37	9.28E-04	NA	NA
ACT [103]	0.1544	0.0025	6.394	1973.35	1.26	8.38E-04	24.25E-03	6.93E-04
SMA [137]	0.1550	0.001	7.295	1545.16	1.07	7.81E-04	NA	6.41E-04
WOA	0.066	0.706	0.1199	1473.43	19.91	2.93E-03	3.38E-04	9.08E-03
GWO	0.083	0.015	0.2424	15.04	45.71	2.92E-03	1.73E-04	8.64E-06
SCA	0.0730	0.01	0.3039	26.3395	68.89	2.05E-03	3.09E-04	8.76E-06
ALO	0.1855	3.573	0.015	3.653	2.15	3.49E-02	2.46E-03	1.23E-03
PSOGSA	0.061	0.05	1.7823	1865.467	1.66	1.72E-02	1.89E-03	9.07E-03
TSA	0.067	4.53	0.9047	291.866	97.52	2.32E-03	1.84E-04	3.09E-04
OTSA	0.1546	0.0177	0.0009	685.75	1.46	**4.48E-06**	**1.69E-04**	**8.25E-06**

6.4.3 Convergence Analysis

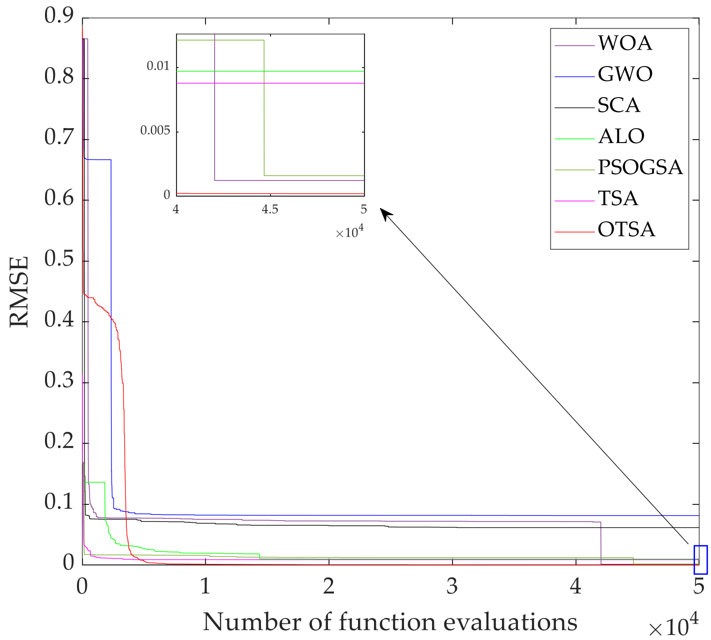
The computational competence of OTSA is investigated through convergence analysis. The convergence curves of SDM for all three PV modules are presented in Figure 6.10. It is depicted in Figure 6.10 that the proposed OTSA algorithm outperforms the WOA, GWO, SCA, ALO, PSOGSA, and TSA algorithms in terms of convergence speed. The OTSA algorithm generates a precise solution for the exact number of function evaluations (i.e., 50000).

For the SS2018PV module, the RMSE values are 1.15E-03, 1.89E-03, 2.18E-03, 1.45E-03, 1.92E-02, 9.73E-04, and 6.83E-04 for WOA, GWO, SCA, ALO, PSOGSA, TSA, OTSA respectively. The RMSE value is minimum for OTSA than that of others. It means that the OTSA decreases the function cost by 30.11 % compared to the basic version of TSA. Similarly, for the SS2018PV module, the RMSE values are 1.23E-03, 8.13E-02, 6.14E-03, 9.70E-02, 1.60E-03, 8.77E-03, and 2.06E-04 for WOA, GWO, SCA, ALO, PSOGSA, TSA, OTSA, respectively. The OTSA algorithm generates a minimum RMSE value than that of others. It indicates that the OTSA decreases the function cost by 97.65% compared to the basic version of TSA. The proposed OTSA method also proves to be competent for the monocrystalline Leibold solar module. The RMSE values are 2.93E-03, 2.92E-03, 2.05E-03, 3.49E-02, 1.72E-02, 2.32E-03 and 4.48E-06 for WOA, GWO, SCA, ALO, PSOGSA, TSA, OTSA respectively. It implies that the OTSA reduced the cost function by 99.80% relative to the standard version of TSA.



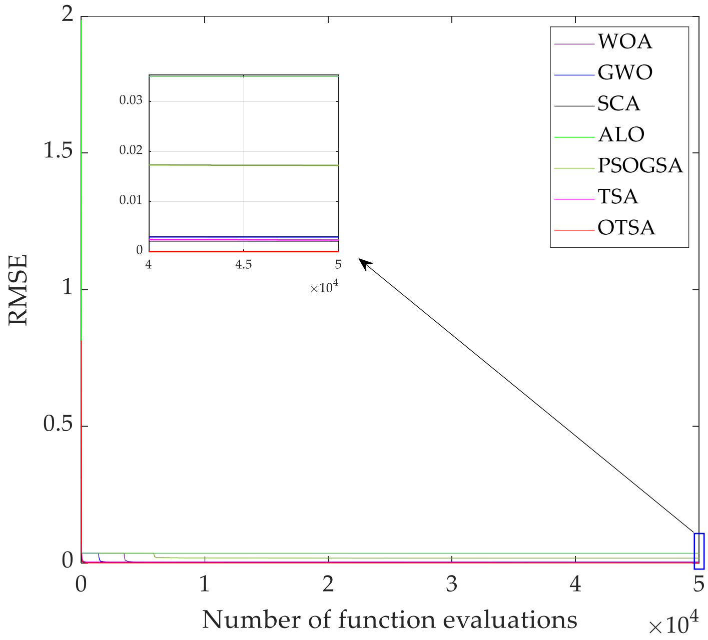
RMSE
Number of function evaluations
×10^4
WOA
GWO
SCA
ALO
PSOGSA
TSA
OTSA

(a)



RMSE
Number of function evaluations
×10^4
WOA
GWO
SCA
ALO
PSOGSA
TSA
OTSA

(b)



(c)

Figure 6.10. Convergence curve of WOAPSO and other six algorithms for SDM of (a) SS2018P PV module (b) SolarexMSX 60 PV module (c) Monocrystalline LSM 20 PV module

6.4.4 Robustness and statistical analysis

This sub-section describes the statistical evaluations based on mean, minimum, maximum, and standard RMSE deviations for OTSA and previously proposed methods. The comparative analysis with the accuracy and reliability of the different algorithms is performed in thirty tests and shown in Table 6.6. The mean of the RMSE is analysed to assess the accuracy of the algorithms, and the standard deviation is determined to analyse the reliability of the proposed parameter estimation technique. The statistical analysis results depict that the proposed OTSA is the most precise and effective parameter estimation technique as it has a very low standard deviation. The Friedman ranking test results are shown in Table 6.7. The best ranking is obtained by the OTSA, followed by TSA, ALO, SCA, WOA, PSOGSA, and GWO.

Table 6.6. Statistical results of RMSE of different algorithms for all three models

PV Module	Algorithm	RMSE			
		Min	Mean	Max	SD
Solarex MSX 60 PV module	WOA	1.23E-03	2.65E-02	2.47E-01	1.04E-02
	GWO	8.13E-02	4.50E-04	2.58E-02	5.81E-03
	SCA	6.14E-02	2.79E-03	4.08E-01	2.31E-04
	ALO	9.71E-02	1.46E-03	3.68E-01	3.31E-03
	PSOGSA	1.60E-03	2.47E-03	3.56E-01	5.47E-03
	TSA	8.77E-03	9.41E-03	3.13E-01	1.69E-03
	OTSA	**2.06E-04**	**2.98E-04**	**1.88E-03**	**1.06E-06**
SS2018P PV module	WOA	1.153E-03	7.32E-03	2.02E-01	1.03E-03
	GWO	1.89E-03	2.68E-03	2.22E-01	3.81E-03
	SCA	2.18E-03	2.74E-03	2.69E-02	3.63E-04
	ALO	1.45E-03	4.07E-03	1.31E-02	4.25E-03
	PSOGSA	1.92E-02	9.45E-03	3.50E-01	1.30E-03
	TSA	9.73E-04	7.75E-03	4.15E-02	2.06E-04
	OTSA	**6.83E-04**	**5.32E-04**	**1.02E-03**	**5.11E-06**
LSM 20 PV module	WOA	2.93E-03	2.62E-03	4.37E-02	2.61E-03
	GWO	2.92E-03	9.92E-02	2.04E-01	9.56E-04
	SCA	2.05E-03	4.31E-03	7.51E-02	1.21E-03
	ALO	3.49E-02	3.52E-04	5.71E-02	7.09E-03
	PSOGSA	1.72E-02	5.77E-03	7.75E-02	8.08E-04
	TSA	2.32E-03	6.65E-04	4.03E-03	5.57E-04
	OTSA	**4.48E-06**	**5.22E-05**	**1.05E-03**	**2.91E-06**

Table 6.7. Ranking of the proposed OTSA and other compared algorithms on three PV modules according to the Friedman test

Algorithms	Friedman Ranking	Final Ranking
WOA	5.06	5
GWO	7.01	7
SCA	4.36	4
ALO	3.23	3
PSOGSA	6.05	6
TSA	2.22	2
OTSA	1	1

6.4.5 Discussion

The OTSA algorithm is successfully developed and implemented for parameter extraction of three PV modules (two polycrystalline and one monocrystalline). The I-V and P-V curves obtained by the optimization process show good agreement with the measured data. The IAE values (both current and power) verify the accuracy of optimized parameters. The statistical analysis shows that the standard deviation is very low for all three PV modules, which confirms that the OTSA is the precise and effective parameter estimation technique. The average execution time of each algorithm on the three PV models is determined and presented in Figure 6.11. Compared to WOA, GWO, SCA, PSOGSA, TSA, OTSA requires a much lower time of about 10 s, while ALO has the worst execution time of about 36 s.

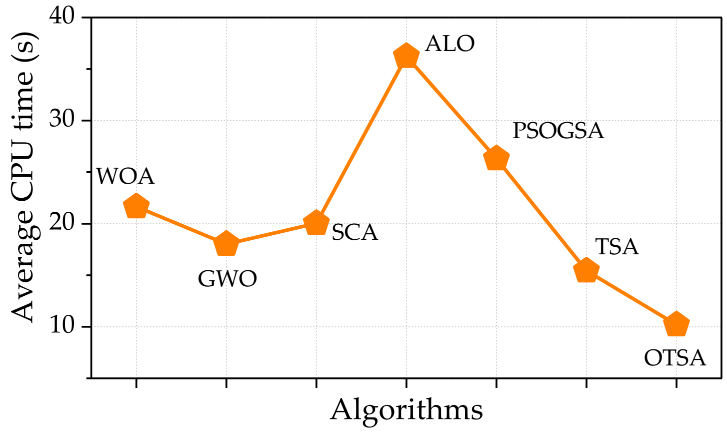


Figure 6.11. Comparison of the execution time of different algorithms

This study proves that the OBL mechanism increases the efficiency of TSA algorithm. Furthermore, additional modification can be done for solving the multi-objective problems.

6.5 Conclusion

In this study, a novel opposition-based tunicate swarm algorithm is successfully developed and analyzed. The proposed algorithm is anticipated to identify the unknown parameters of photovoltaic modules precisely and effectively.

- The proposed OTSA performed adequately and is reliable in terms of RMSE, SAE, and MAE compared to other methodologies such as WOA, GWO, SCA, ALO, PSOGSA, TSA, and similar approaches available in the literature.
- The implementation of OTSA leads to a reduction in cost function by 30.11%, 97.65%, and 99.80 % for SS2018, SolarexMSX 60, and LSM 20 PV module, respectively, as compared with the basic TSA. Based on the performance at different irradiation levels, the OTSA also establishes a more reliable efficacy.
- The OTSA algorithm produces the least value of RMSE even at 360 W/m^2. The convergence curves reveal that the OTSA algorithm obtains the finest values of estimated parameters for all three PV modules.

Although the effectiveness of the proposed approach for estimating PV parameters has been demonstrated by statistical analysis, there are still a few constrained factors that could be further considered for future works. First, the proposed OTSA can be implemented for various other solar cell models to prove its capability. It can be used to observe the effect of unpredictable external factors like wind, rain, etc. Second, the feasibility of the proposed OTSA can be further enhanced based on other optimization techniques and concepts. The authors would like to mention that OTSA cannot be recognized as a ubiquitous method because no such approach exists that can solve all optimization problems as per the statement of the NFL theorem.

CHAPTER 7

CONCLUSION

The renewable sources have become an attractive option due to the rising cost of the fossil fuels and due to the inevitable and unavoidable depletion of these fuel reserves, along with the disquieting pollution problem and growing concerns for climate change. In response to these challenges new and effective cleaner energy sources have been the center of attraction. Among these sources, the electricity generation capacity via PV systems has enormously grown in recent decades. Detailed modelling of PV system is normally essential for addressing these problems effectively. Estimation of parameters from experimental data rather than from the values given in manufacturers' data sheets at STC, has received attention of research professionals in recent years. The present research work is divided into seven chapters.

The first chapter discussed the current scenario of solar PV system and the role of PV system in generation of clean energy. This chapter discusses about how the metaheuristic techniques can be used to optimize solar cell/module parameters. Earlier work on this is also revived in order to provide the problem with a firm basis. The second chapter presents a brief literature review of various metaheuristic algorithms developed earlier to solve various issues related to parameter optimization of solar cells. The pertinency and weaknesses of these algorithms are revealed. It is determined that each algorithm is established on the foundation of numerous natural activities of diverse living entities. Looking at the harshness of the problems, these algorithms are improved. A comparative analysis of applicability and consequences of these algorithms are provided in this chapter. It is reported that all the algorithms are not suitable for each problem, instead for each problem different algorithms have to be developed.

The third chapter introduces the details of implementation of GWO algorithm for the parameter estimation of SDM and DDM for solar cell (RTC France) at standard temperature condition. The comparison of implemented GWO algorithm is carried out with PS, SA, HS, PSO, GA. Furthermore, a comparison in terms of error in voltage, current and power is also performed for the validation of GWO algorithm.

The fourth chapter presents and discusses the simulation results of TSA algorithm for parameter estimation of PWP201 PV module at STC (standard temperature conditions). It should be noted that TSA is first time implemented for the problem of parameter estimation of solar panels. In addition to this the effectiveness and accuracy of TSA is compared with GSA, WOA, SCA and PSOGSA. TSA proves its competency in terms of RMSE (taken as objective function). Chapter five represents the implementation of newly developed hybrid version of PSO and WOA i.e., WOAPSO algorithm for the parameter estimation of solar cell (at STC) and SS2018P PV module (under different levels of irradiance i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2. In proposed WOAPSO algorithm the exploitation ability of PSO is implemented in pipeline mode when WOA stops to improve the best-found solution. The collaboration of both metaheuristic algorithms is able to establish an effective balance between exploitation and exploration search ability.

The Chapter six introduces the implementation of a newly anticipated OTSA algorithm for the parameter estimation of SDM of two different kinds: polycrystalline and monocrystalline PV panels. Three objective functions: RMSE, MAE and SAE are considered for the optimization. In OTSA, author has combined the OBL mechanism for initialization of search agents. The integration of OBL does not influence the basic functionality of TSA, and the precision of the optimal solution is enhanced. In this manner, OTSA can limit the number of the initial population, which improves the convergence to the optimal solution since it's exploring the solution space for an optimization problem. The present seventh chapter summarizes, concludes and proposed the future work in the field of parameter estimation of solar cell/module.

7.1 Findings and Conclusion

- GWO is compared with five pre-existing and well-established algorithms in the literature, they are PS, SA, HS, PSO and GA. Simulation results clearly indicates that the best values of estimated parameters are obtained by GWO, and RMSE is 9.4094E- 04 and 1.2450E- 03 in the case of SDM and DDM respectively.

- In the case of SDM, the best values of I_m, V_m and P_m are obtained by GWO algorithm as 67.46 A, 45.9 V and 30.96 W respectively. Moreover, GWO provided the improved FF of 1.46%. The highest values of I_m, V_m and P_m are achieved by the GWO algorithm as 67.66 A, 45.9 V and 31.05 W accordingly, the case of DDM. In addition to this, GWO also produced the improved FF of 1.83%.
- TSA is relatively accurate and reliable at delivering the solution in terms of RMSE as compared with other algorithms such as GSA, PSOGSA, SCA, and WOA. The statistical analysis depicts the robustness of the TSA technique on parameter estimation problem under standard operating conditions. The convergence curves demonstrate that the best values of estimated parameters are obtained by TSA in terms of RMSE is 5.06E-04.
- The proposed WOAPSO is relatively accurate and reliable at delivering the solution in terms of RMSE as compared with other algorithms such as GSA, SCA, GWO, PSO, WOA, PSOGSA, and existing algorithms in the literature. The convergence curves demonstrate that the best values of estimated parameters are obtained by WOAPSO, and RMSE is 7.1700E-04 and 9.8412E-04 in the case of SDM and DDM respectively.
- At different irradiation levels (i.e., 1000 W/m^2, 870 W/m^2, 720 W/m^2, and 630 W/m^2), the proposed WOAPSO algorithm is best in producing optimized parameters (I_p, I_{sd}, a, R_s, R_{sh}) and minimum value of RMSE for PV module even at a low level of irradiation (630 W/m^2).
- The proposed OTSA performed adequately and is reliable in terms of RMSE, SAE, and MAE compared to other methodologies such as WOA, GWO, SCA, ALO, PSOGSA, TSA, and similar approaches available in the literature. The implementation of OTSA leads to a reduction in cost function by 30.11%, 97.65%, and 99.80 % for SS2018, SolarexMSX 60, and LSM 20 PV module, respectively, as compared

with the basic TSA. Based on the performance at different irradiation levels, the OTSA also establishes a more reliable efficacy.

- The OTSA algorithm produces the least value of RMSE even at 360 W/m^2. The convergence curves reveal that the OTSA algorithm obtains the finest values of estimated parameters for all three PV modules.

7.2 Scope of Future work

The present research work covered various aspects of metaheuristics algorithms which includes different approaches for parameter estimation of solar cell/ module. But still their remains certain opportunities to extend the scope of this thesis work. Although the effectiveness of the proposed approach for estimating PV parameters has been demonstrated by statistical analysis, there are still a few constrained factors that could be further considered for future works. First, the proposed metaheuristic techniques can be implemented for various other solar cell models to prove its capability. It can be used to observe the effect of unpredictable external factors like wind, rain, etc. Second, the feasibility of the proposed techniques can be further enhanced based on other optimization techniques and concepts. The authors would like to mention that anticipated algorithms in this research work cannot be recognized as a ubiquitous method because no such approach exists that can solve all optimization problems as per the statement of the NFL theorem.

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APPENDIX

Table A1. Measured values of current and voltage for solar PV panel at different irradiance level.

Voltage *(V)*	Current *(Amp)*			
	1000 w/m^2	**870w/m^2**	**@720 w/m^2**	**630 w/m^2**
0.08448	1.169782	1.017777	0.842277	0.736977
0.255877	1.169753	1.017682	0.842182	0.736882
0.555023	1.16975	1.017653	0.842153	0.736853
1.089629	1.169752	1.01765	0.84215	0.73685
2.152909	1.16975	1.017652	0.842152	0.736852
2.878082	1.169754	1.01765	0.84215	0.73685
3.869691	1.169748	1.017654	0.842154	0.736854
4.583331	1.169751	1.017648	0.842148	0.736848
5.548299	1.169742	1.017651	0.842151	0.736851
6.278014	1.169738	1.017642	0.842142	0.736842
7.224307	1.169719	1.017638	0.842138	0.736838
8.050157	1.169684	1.017619	0.842119	0.736819
8.787816	1.169625	1.017584	0.842084	0.736784
9.768923	1.169502	1.017525	0.842025	0.736725
10.5181	1.169288	1.017402	0.841902	0.736602
11.3167	1.168853	1.017188	0.841688	0.736388
12.19018	1.16809	1.016753	0.841253	0.735953
12.99476	1.166352	1.01599	0.84049	0.73519
13.94578	1.163882	1.014252	0.838751	0.733451
14.65562	1.158313	1.011781	0.836281	0.73098
15.53478	1.147141	1.006212	0.83071	0.72541
16.43301	1.13126	0.995038	0.819535	0.714233
17.13243	1.090734	0.979155	0.80365	0.698347

18.08016	1.032567	0.938625	0.763114	0.657808
18.80656	0.890636	0.880451	0.704933	0.599622
19.74234	0.649391	0.738504	0.562967	0.457644
20.56286	0	0	0	0

Table A2. Comparison of WOAPSO with different parameter estimation methods for SDM.

Algorithms	I_{ph}(A) ± SD	I_{sd} (μA) ± SD	R_s (Ω) ± SD	R_{sh} (Ω) ± SD	a± SD	RMSE
HISA [138]	1.0324	2.6773	1.2317	748.4507	47.6575	2.0166E−03
CS [36]	0.7605	0.3602	0.0349	43.8423	1.4929	2.0119E−03
BLPSO [139]	0.7607	0.3662	0.0359	60.2845	1.4939	1.0272E−03
SA [68]	0.762	0.4798	0.0345	43.1034	1.5172	1.7000E−03
mGWO [35]	0.7606	0.3853	0.0356	64.6624	1.4991	1.1278E−03
GOTLBO[140]	0.7608	0.3315	0.0362	54.1154	1.4838	9.8744E−04
BMO [127]	0.7608	0.3248	0.0364	53.8716	1.4817	9.8602E−04
MLBSA [141]	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E−04
EHHO [142]	0.7607	0.3230	0.0363	53.7428	1.4812	9.8602E-04
IJAYA [92]	0.7608	0.3228	0.0364	53.7595	1.4811	9.8603E-04
GOTLBO [91]	0.7608	0.3315	0.0362	54.1154	1.4838	9.8744E-04
WOAPSO	0.7597±0.0012	0.499±0.004	0.0342±0.0007	83.0131±0.027	1.5483±0.001	**7.1700E-04**

Table A3. The calculated current and absolute error results of WOAPSO for SDM.

Observations	Measured data		Simulated current data		Simulated power data	
	V_L (V)	I_L (A)	I_{sim} (A)	IAE (A)	P_{sim} (W)	IAE (W)
1	0.0057	0.7605	0.7609	0.0004	0.0043	0
2	0.0646	0.76	0.7596	0.0004	0.0491	0
3	0.1185	0.759	0.7584	0.0006	0.0898	0.0001
4	0.1678	0.757	0.7574	0.0004	0.1271	0.0001
5	0.2132	0.757	0.7563	0.0007	0.1612	0.0002
6	0.2545	0.7555	0.7552	0.0003	0.1922	0.0001
7	0.2924	0.754	0.7536	0.0004	0.2204	0.0001
8	0.3269	0.7505	0.7513	0.0008	0.2456	0.0003
9	0.3585	0.7465	0.7472	0.0007	0.2679	0.0003
10	0.3873	0.7385	0.74	0.0015	0.2866	0.0006
11	0.4137	0.728	0.7273	0.0007	0.3008	0.0003
12	0.4373	0.7065	0.7069	0.0004	0.3091	0.0011
13	0.459	0.6755	0.6752	0.0003	0.3099	0.0002
14	0.4784	0.632	0.6307	0.0013	0.3017	0.0006
15	0.496	0.573	0.5718	0.0012	0.2836	0.0006

16	0.5119	0.499	0.4994	0.0004	0.2557	0.0003
17	0.5265	0.413	0.4134	0.0004	0.2177	0.0003
18	0.5398	0.3165	0.3273	0.0018	0.1767	0.0059
19	0.5521	0.212	0.2122	0.0002	0.1172	0.0002
20	0.5633	0.1035	0.1028	0.0007	0.0579	0.0004
Sum of IAE				0.0136		0.0117

Table A4. Comparison of WOAPSO with different parameter estimation methods for DDM.

Algorithms	I_{ph}(A)±SD	I_{sd1}(μA)± SD	I_{sd2}(μA)± SD	R_s (Ω)± SD	R_{sh} (Ω)± SD	a_1± SD	a_2± SD	RMSE
HISA [138]	1.03236	2.64194	1.00E−09	1.2317	748.4507	47.6574	47.6325	2.0166E-03
CS [36]	0.76223	0.02732	0.50832	0.0353	97.73242	1.70274	1.52893	2.4440E-03
BLPSO [139]	0.76056	0.17895	0.3156	0.0355	64.79937	1.69574	1.48789	1.1042E-03
SA [68]	0.7623	0.4767	0.01	0.0345	43.1034	1.5172	2	1.9000E-02
mGWO [35]	0.76088	0.49333	0.17345	0.0346	62.17868	1.52522	1.94264	1.3163E-03
GOTLBO[140]	0.7602	0.9889	0.0001	0.032	81.3008	1.6	1.192	1.52E-02
BMO [127]	0.7608	0.0001	0.0001	0.0364	53.7185	1.3355	1.481	3.60E-01
MLBSA [141]	0.7608	0.22728	0.73835	0.0367	55.4612	1.4515	2	**9.8249E-04**
EHHO [142]	0.76076	0.5861	0.2409	0.0365	55.6394	1.9684	1.4569	**9.8360E-04**
IJAYA [92]	0.7601	0.00504	0.7509	0.0376	77.8519	1.2186	1.6247	**9.8293E-04**
GOTLBO [91]	0.760752	0.80019	0.22046	0.03678	56.0753	1.9999	1.4489	**9.8317E-04**
WOAPSO	0.7601±0.0007	0.5±0.0020	0.5±0.0027	0.0311±0.0005	100±0.4345	1.5755±0.0043	1.7314±0.0015	**9.8412E-04**

Table A5. The calculated current and absolute error results of WOAPSO for DDM.

Observations	Measured data		Simulated current data		Simulated power data	
	V_L (V)	I_L (A)	I_{sim} (A)	IAE (A)	P_{sim} (W)	IAE (W)
1	0.0057	0.7605	0.7588	0.0017	0.0043	0
2	0.0646	0.76	0.7582	0.0018	0.0489	0.0002
3	0.1185	0.759	0.7577	0.0013	0.0898	0.0001
4	0.1678	0.757	0.7571	0.0001	0.127	0
5	0.2132	0.757	0.7566	0.0004	0.1613	0.0001
6	0.2545	0.7555	0.7558	0.0003	0.1924	0.0001
7	0.2924	0.754	0.7546	0.0006	0.2206	0.0001
8	0.3269	0.7505	0.7524	0.0019	0.2459	0.0006
9	0.3585	0.7465	0.7484	0.0019	0.2681	0.0005
10	0.3873	0.7385	0.7409	0.0024	0.2869	0.0009
11	0.4137	0.728	0.7279	0.0001	0.3011	0.0001
12	0.4373	0.7065	0.707	0.0005	0.3092	0.0003
13	0.459	0.6755	0.6748	0.0007	0.3097	0.0004
14	0.4784	0.632	0.6298	0.0022	0.3013	0.001
15	0.496	0.573	0.5706	0.0024	0.283	0.0012

16	0.5119	0.499	0.4981	0.0009	0.2549	0.0005
17	0.5265	0.413	0.4122	0.0008	0.217	0.0005
18	0.5398	0.3165	0.3262	0.0097	0.1761	0.0053
19	0.5521	0.212	0.2117	0.0003	0.1169	0.0001
20	0.5633	0.1035	0.1027	0.0008	0.0578	0.0005
Sum of IAE				0.0308		0.0125

Table A6. The calculated current and absolute error results of WOAPSO for Solar PV Module (630 W/m^2).

Parameters	Algorithms						
	GSA	**SCA**	**GWO**	**PSO**	**WOA**	**PSOGSA**	**WOAPSO**
Iph (A)	0.6710 ±0.0105	0.7399 ±0.0113	0.7397 ±0.037	0.7419 ±0.252	0.7421 ±0.0043	0.6706 ±0.252	0.7382 ±0.0008
Isd (µA)	5.00E-05 ±5.697	2.80E-08 ±0.316	1.00E-08 ±0.858	1.00E-08 ±0.053	4.37E-07 ±0.522	1.18E-05 ±0.6745	0.0118 ±0.023
Rs (Ω)	0.001 ±0.0695	0.0249 ±0.0412	0.0276 ± 0.59	0.0265 ±0.054	0.0017 ±0.0114	0.2810 ±0.107	0.0273 ± 0.0176
Rsh (Ω)	1206.82 ±12.31	768.387 ±18.99	99.25 ±14.24	1084.907 ±21.61	54.124 ±29.7363	657.23 ±0.834	248.708 ±0.1088
a	65.3725 ± 1.422	1.3298 ±6.366	1.2552 ±0.0217	1.2553 ±1.352	1.5841 ±4.708	99.77 ±0.452	1.2665 ±0.1106
RMSE	2.43E-01	9.54E-02	9.48E-02	1.30E-01	9.70E-03	1.33E-02	8.8226E-03
CPU Time (s)	14.05	18.06	16.01	13.21	11.27	19.23	8.53

Table A7. The calculated current and absolute error results of WOAPSO for Solar PV Module (720 W/m^2).

Parameters	Algorithms

	GSA	SCA	GWO	PSO	WOA	PSOGSA	WOAPSO
Iph (A) ±SD	0.7802± 0.0044	0.8486±0.0179	0.8449± 0.0206	0.9561±0.021	0.8487±0.0049	0.766±0.027	0.8421±0.0012
Isd (μA) ±SD	1.00E-08±0.237	5.60E-08±0.4365	6.98E-08±0.869	1.58E-08±0.301	1.50E-07±1.501	1.22E-05±0.234	0.0022±0.043
Rs (Ω) ±SD	0.001± 0.0212	0.0019±0.0123	0.00566±0.037	0.0028±1.052	0.0011± 0.044	0.122±0.013	0.0117±0.0002
Rsh (Ω) ±SD	404.42±13.82	28.007± 21.44	92.4964±17.699	91.882±1.431	38.915±44.49	122.4471± 12.02	1870.72± 4.924
a±SD	45.964±0.2528	1.3776±13.33	1.3954±0.1772	2.2658±1.352	1.4645±2.1847	6.0933±0.1420	1.3022±0.0402
RMSE	1.94E-01	7.16E-03	3.15E-02	6.54E-03	1.70E-03	9.29E-03	1.795E-03
CPU Time (second)	15.39	15.17	12	11.05	9.71	17.13	8.11

Table A8. The calculated current and absolute error results of WOAPSO for Solar PV Module (870 W/m^2).

Parameters	Algorithms						
	GSA	SCA	GWO	PSO	WOA	PSOGSA	WOAPSO
Iph (A)	0.9506 ± 0.0056	1.018 ±0.0119	1 ±0.064	0.8834 ±1.334	1.029 ± 0.019	0.943 ±0.023	1.0179 ±0.0014
Isd (μA)	5.00E-05 ± 1.130	3.48E-08 ±0.634	1.00E-08 ±0.516	3.98E-05 ±1.165	6.91E-08 ±0.804	2.86E-05 ±0.623	0.0689 ±0.0852
Rs (Ω)	0.001 ±0.0328	0.0012 ±0.03	0.0038 ± 0.809	1.4099 ±0.381	0.0015 ± 0.0294	0.6977 ±0.034	0.001 ±0.0201
Rsh (Ω)	670.255 ±14.10	72.656 ±16.02	100 ±2.4565	1092.74 ±1.33	21.489 ±39.10	1027.49 ±0.27	537.47 ±0.0281
a	58.4639 ± 0.2469	1.3339 ± 2.342	1.2442 ± 0.0152	100 ±0.707	1.391 ±2.0765	33.859 ±0.143	1.3882 ±0.0124
RMSE	1.84E-01	3.59E-03	1.70E-02	5.01E-03	1.41E-03	4.02E-03	3.7957E-04
CPU Time (s)	16.02	14.25	9.25	12	15.005	8.16	8.05

Table A9. The calculated current and absolute error results of WOAPSO for Solar PV Module.

Observations	Measured data		Simulated current data		Simulated power data	
	V_L (V)	I_L (A)	I_{sim} (A)	IAE (A)	P_{sim} (W)	IAE (W)
1	0.0845	1.1698	1.1707	0.0009	0.0989	0.0001
2	0.2559	1.1698	1.1707	0.0009	0.2996	0.0003
3	0.555	1.1698	1.1707	0.0009	0.6498	0.0006
4	1.0896	1.1697	1.1706	0.0009	1.2755	0.0009
5	2.1529	1.1696	1.1704	0.0008	2.5199	0.0015
6	2.8781	1.1697	1.1703	0.0006	3.3683	0.0017
7	3.8697	1.1698	1.1701	0.0003	4.5282	0.0016
8	4.5833	1.1697	1.1701	0.0004	5.3628	0.0015
9	5.5483	1.1697	1.1699	0.0002	6.491	0.0009
10	6.278	1.1697	1.1698	0.0001	7.344	0.0003
11	7.2243	1.1697	1.1696	0.0001	8.4498	0.0007
12	8.0502	1.1697	1.1695	0.0002	9.4146	0.0018
13	8.7878	1.1696	1.1694	0.0002	10.276	0.0029
14	9.7689	1.1696	1.1691	0.0005	11.4211	0.0048
15	10.5181	1.1695	1.1689	0.0006	12.2947	0.0062
16	11.3167	1.1692	1.1686	0.0006	13.2245	0.008
17	12.1902	1.1688	1.168	0.0008	14.2386	0.0099
18	12.9948	1.168	1.1672	0.0008	15.1673	0.0118
19	13.9458	1.1663	1.1654	0.0009	16.2517	0.014
20	14.6556	1.1638	1.1629	0.0009	17.0431	0.0143
21	15.5348	1.1583	1.1574	0.0009	17.9798	0.0143
22	16.433	1.1471	1.1464	0.0007	18.8385	0.0124
23	17.1324	1.1313	1.1308	0.0005	19.3732	0.008

24	18.0801	1.0907	1.0908	0.0001	19.722	0.0014
25	18.8066	1.0326	1.0332	0.0006	19.4314	0.0124
26	19.7423	0.8906	0.8919	0.0013	17.6081	0.0249
27	20.5629	0.6494	0.6503	0.0009	13.3722	0.0189
28	21.3013	0.2582	0.2564	0.0018	5.4626	0.0381
Sum of IAE				0.0184		0.2148

Table A10. Measured values of current and voltage for Solarex MSX 60 solar PV panel at different irradiance level.

Voltage *(V)*	Current *(Amp)*		
	1000 w/m^2	**750w/m^2**	**500 w/m^2**
0	3.8174	2.8656	1.9121
0.8115	3.8015	2.8557	1.9069
1.6230	3.7944	2.8500	1.9027
2.4346	3.7855	2.8434	1.8984
3.2461	3.7769	2.8369	1.8941
4.0576	3.7683	2.8305	1.8898
4.8692	3.7597	2.8240	1.8855
5.6807	3.7511	2.8175	1.8811
6.4923	3.7425	2.8111	1.8768
7.3038	3.7339	2.8046	1.8725
8.1153	3.7253	2.7982	1.8682
8.9269	3.7167	2.7917	1.8639
9.7384	3.7081	2.7852	1.8596
10.5500	3.6995	2.7788	1.8553
11.3615	3.6909	2.7723	1.8509
12.1730	3.6823	2.7658	1.8466
12.9846	3.6736	2.7593	1.8423
13.7961	3.6646	2.7527	1.8379
14.6076	3.6548	2.7457	1.8334
15.4192	3.6415	2.7373	1.8282
16.2307	3.6158	2.7233	1.8207
17.0423	3.5464	2.6895	1.8044
17.8538	3.3461	2.5887	1.7567

18.6653	2.8771	2.3068	1.6088
19.4769	2.1119	1.7225	1.2260
20.2884	1.1577	0.8761	0.5327
21.1	0.0847	-0.1274	-0.3799

TABLE A11. Comparison of OTSA with different parameter estimation methods for Solarex MSX-60 PV module (750 w/m^2, 25° C)

Algorithms	**I_{ph} (A)**	**I_{sd} (μA)**	**R_s (Ω)**	**R_{sh} (Ω)**	**a**	**RMSE**	**SAE**	**MAE**
WOA	1.1755	0.955	0.001	124.17	1.67	2.665E-03	6.593E-05	1.203E-03
GWO	1.1701	0.068	0.0013	524.67	1.39	9.9954E-04	1.7584E-05	5.244E-08
SCA	1.166	0.055	0.002	176.73	1.37	1.736E-03	2.681E-04	1.612E-05
ALO	1.171	0.027	0.006	188.65	1.32	4.51E-03	7.72E-04	1.415E-06
PSOGSA	1.091	0.05	0.512	738.74	42.17	1.173E-02	5.513E-02	1.241E-04
TSA	1.171	0.005	0.001	135.74	1.36	8.8834E-04	1.652E-05	3.779E-07
OTSA	1.1696	0.0697	0.001	1736.56	1.3	**4.97E-04**	**8.50E-09**	**9.09E-08**

TABLE A12. Comparison of OTSA with different parameter estimation methods for Solarex MSX-60 PV module (500 w/m^2, 25° C)

Algorithms	**I_{ph} (A)**	**I_{sd} (μA)**	**R_s (Ω)**	**R_{sh} (Ω)**	**a**	**RMSE**	**SAE**	**MAE**
WOA	1.175	0.0373	0.024	83.65	1.56	6.789E-03	2.24E-03	8.316E-03
GWO	1.172	0.056	0.075	92.14	1.37	1.217E-03	9.3025E-06	1.603E-07

SCA	1.1707	0.01	0.016	384.56	1.25	3.816E-03	2.436E-04	2.369E-05
ALO	1.158	0.4931	0.067	1690.71	2.41	3.755E-02	1.293E-03	2.301E-03
PSOGSA	1.151	0.05	0.524	1140.90	1.5	1.127E-02	3.498E-02	3.77E-02
TSA	1.1701	0.0635	0.009	449.00	1.38	2.3615E-03	2.237E-05	8.023E-08
OTSA	1.1708	0.007	0.0001	188.23	1.38	**3.54E-04**	**1.16E-08**	**2.73E-08**

TABLE A13. Comparison of OTSA with different parameter estimation methods for SS2018 PV module (870 w/m^2, 25° C).

Algorithms	**I_{ph} (A)**	**I_{sd} (μA)**	**R_s (Ω)**	**R_{sh} (Ω)**	**a**	**RMSE**	**SAE**	**MAE**
WOA	0.9481	0.05	1.708	668.01	19.85	7.83E-03	1.08E-03	3.45E-04
GWO	1.059	0.0143	0.001	1180.942	2.46	5.63E-03	4.62E-04	2.80E-05
SCA	0.951	0.015	1.851	2000	14.70	9.83E-03	1.16E-03	3.799E-03
ALO	1.017	0.0747	0.005	1761.26	2.39	1.262-03	2.41E-04	2.25E-04
PSOGSA	1.017	0.05	1.706	736.90	30.39	1.067E-02	9.12E-03	1.64E-04
TSA	1.099	0.0451	1.592	1210.023	50.92	9.62E-04	6.91E-07	9.75E-05
OTSA	1.017	0.0689	0.0008	1118.262	1.38	**7.14E-04**	**3.75E-09**	**3.10E-07**

TABLE A14. Comparison of OTSA with different parameter estimation methods for SS2018 PV module (720 w/m^2, 25° C).

Algorithms	**I_{ph} (A)**	**I_{sd} (μA)**	**R_s (Ω)**	**R_{sh} (Ω)**	**a**	**RMSE**	**SAE**	**MAE**
WOA	0.7752	0.0396	0.013	289.7547	82.8638	2.05E-03	6.45E-03	1.172E-03
GWO	0.7821	0.01	0.001	780.2238	100	4.13E-03	2.15E-03	1.66E-04
SCA	0.7520	0.05	0.001	1826.015	80.3064	1.86E-02	8.53E-02	3.443E-03
ALO	0.8289	0.0351	1.1435	142.7765	65.7787	3.692E-03	8.07E-04	3.792E-04
PSOGSA	0.7786	0.05	1.9948	1211.499	47.9382	9.78E-03	6.23E-04	2.08E-04
TSA	0.7828	0.607	0.8882	140.6266	77.9108	3.11E-04	5.86E-04	3.26E-05
OTSA	0.844	0.185	0.0002	140.03	1.4	**5.98E-06**	**2.51E-04**	**1.98E-05**

List of Publications

1. Abhishek *et al.* “An Effective Method for Parameter Estimation of Solar PV Cell Using Grey-Wolf Optimization Technique”, International Journal of Mathematical, Engineering and Management Sciences, 2021, 6 (3), 10.33889/IJMEMS.2021.6.3.054, (ESCI-indexed).
2. Sharma, Abhishek, et al. "Parameter Extraction of Photovoltaic Module Using Tunicate Swarm Algorithm." *Electronics* 10.8 (2021): 878. 10.3390/electronics10080878, (SCI-Indexed, IF- 2.3).
3. Sharma, Abhishek, et al. "An effective method for parameter estimation of a solar cell." Electronics 10.3 (2021): 312. 10.3390/electronics10030312, (SCI-Indexed, IF- 2.3).
4. Sharma, Abhishek, et al. “Opposition-based Tunicate Swarm Algorithm for Parameter Optimization of Solar Cells”. IEEE Acess, 10.1109/ACCESS.2021.3110849, (SCI-Indexed, IF- 3.3).

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Curriculum vitae

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TECHNICAL SKILLS

- Programming: MATLAB, ROS, C/C++, Python, Embedded C,
- Robotics Software: V-Rep Edu, Webots, Atmega-platform, Arduino platform, Arm Processor.
- Designing and fabrication from 3D printer (Miicraft).
- Operating Systems: Linux, Windows.
- Design Software Packages: Winavr, Proteus, Diptrace, PCB wizard, Rhinoceros.
- Debugging of Hardware Related problems on designed PCB boards.

WORK EXPERIENCE

1. **Research Scientist (January 2019- till date)**
   University of Petroleum and Energy Studies, Dehradun (India)
   Achievement – 10 Journal paper, 2 book chapters, 1 patent (granted), 2 books (under publication process)

2. **Research Scholar (January 2017- July 2018)**
   Ariel University, Israel
   Achievement – 1 Journal paper (Accepted)

3. **Assistant Professor (August 2015—December 2016)**
   University of Petroleum and Energy Studies, Dehradun (India)
   Achievement - 1 Patent, 2 Journal paper, 5 Conference paper (International)

4. **Junior Research Fellow (November 2014—July 2015)**
   University of Petroleum and Energy Studies, Dehradun (India)
   Title - Micro-Fluidic Lab-on-chip sensor to detect and monitor viscosities for a variety of Biochemical Applications.
   Funding Body - Department of Science and Technology, Government of India
   Achievement - 1 Patent, 1 Journal Paper, 1 Conference Paper (International)

ADMINISTRATIVE WORK EXPERIENCE

1. Successfully handled and maintained the consultancy data (criteria 3.5.1) and MoU data (criteria 3.7.3) for NAAC.

2. Design and development of policies (like consultancy, MoU) and course structure for the university.

3. Organization of workshops, seminars, and conferences for the university.

EDUCATIONAL BACKGROUND

Year(s)	**Qualification – Degree / Diploma / Certificate**	**Board/University**	**College / Institute/ University**	**Percentage / CGPA**
2019	Ph. D (pursuing)	University of Petroleum & Energy Studies, Dehradun	College of Engineering Studies, India	1. Course work-7.9/10 2. Thesis (in advance stage)
2014	M.Tech (Robotics Engineering)	University of Petroleum & Energy Studies, Dehradun	College of Engineering Studies, India	3.1/4
2012	B. Tech (Electronics and Communication)	R.G.T.U	I.T.M University, Gwalior, India	72%
2007	12th	CBSE	T.I.C , Etawah(U.P.), India	80%
2005	10th	CBSE	T.I.C , Etawah(U.P.), India	82%

PATENTS

1. **Title:** Moveable washbasin (India). **Status:** ***Granted***
   Application number: 331814-001.

2. **Title:** An Optofluidic Micro-viscometer for measuring Adulteration in a Fluid (India).
   Status: *Published*
   Application number: #780/DEL/2015

3. **Title:** A system and method for locating an injured or a non-responsive person (India).
   Status: *Published*
   Application number: 2070/DEL/2014

4. **Title:** Patient Health Monitoring and Tracking System (India).
   Status: *Published*
   Application number: 201611039333

5. **Title:** System for Prevention of Traffic Collisions and Method Thereof (India)
   Status: *Published*
   Application number: 202011011550A

PUBLICATIONS

1. **Abhishek Sharma,** Abhinav Sharma, Ankit Dasgotra, Vibhu Jately, Mangey Ram, Shailendra Rajput, Moshe Averbukh, Brian Azzopardi "Opposition-based Tunicate Swarm Algorithm for Parameter Optimization of Solar Cells", IEEE Access, (SCI-indexed), **Impact Factor- 3.3 (2021)**

2. **Abhishek Sharma**, Abhinav Sharma, Moshe Averbukh, Vibhu Jately, Brian Azzopardi "An Effective Method for Parameter Estimation of a Solar Cell", Electronics, (SCI-indexed), **Impact Factor- 2.3 (2021)**

3. **Abhishek Sharma**, Shraga Shoval, Abhinav Sharma, Jitendra K Pandey "Path planning for multiple targets interception by the swarm of UAVs based on Swarm Intelligence (SI) algorithms: A Review". IETE Technical Review, (SCI-indexed), **Impact Factor- 1.8 (2021)**

4. Abhishek Sharma, Ankit Dasgotra, Sunil Kumar Tiwari, Abhinav Sharma, Vibhu Jately, Brian Azzopardi, "Parameter Extraction of Photovoltaic Module Using Tunicate Swarm Algorithm", Electronics, (SCI-indexed), **Impact Factor- 2.3 (2021)**

5. Nikhil Raj, Ankit Dasgotra, Vishal Kumar Singh, Surajit Mondal, **Abhishek Sharma**, Jitendra K Pandey "A Novel Method of Mass Disinfection for the Prevention of Covid-19", IJCRR, (ESCI-Indexed) **(2021)**

6. **Abhishek Sharma**, Abhinav Sharma, Averbukh Moshe, Nikhil Raj, Rupendra Kumar Pachauri "An Effective Method for Parameter Estimation of Solar PV Cell Using Grey-Wolf Optimization Technique", IJMEMS (ESCI-Indexed) **(2021)**

7. Abhinav Sharma, R. Gowri, Vinay Chowdary, **Abhishek Sharma**, Vibhu Jately "Maximum Likelihood Direction of Arrival Estimation using Chicken Swarm Optimization Algorithm", IJMEMS (ESCI-Indexed) **(2021)**

8. Jyoti Bansal, **Abhishek Sharma**, "Challenges & Issues for 21st Century in Indian context to Accreditation & Quality Control: A Review", Psychology and Education, (Scopus-Indexed) **(2021)**

9. Yunkun Tao, Jianbo Bai, Rupendra Kumar Pachauri, **Abhishek Sharma** "Parameter extraction of photovoltaic modules using a heuristic iterative algorithm", Energy Conversion and Management, (SCI-indexed), **Impact Factor- 9.7 (2020)**

10. Rupendra Kumar Pachauri, Om Prakash Mahela, **Abhishek Sharma**, Jianbo Bai, Yogesh K Chauhan, Baseem Khan, Hassan Haes Alhelou, "Impact of Partial Shading on Various PV Array Configurations and Different Modeling Approaches: A Comprehensive Review". IEEE Access (SCI-indexed), **Impact**

Factor- 3.3 **(2020)**

11. **Abhishek Sharma**, Surajit Mondal, Amit Kumar Mondal, Soumadeep Baksi, Ravi Kumar Patel, Won-Shik Chu, Jitendra K Pandey, "3D printing, its intrinsic microfluidic functions and environmental impacts", International Journal of Precision Engineering and Manufacturing- Green Technology (SCI-indexed), **Impact Factor-5.6 (2017)**

12. Venkateswaran, P.S., **Abhishek Sharma**, Santosh Dubey, Ajay Agarwal and Sanket Goel, "Rapid and Automated Measurement of Milk Adulteration using a 3D Printed Optofluidic Microviscometer (OMV)", IEEE Sensors Journal (SCI-indexed), **Impact Factor- 3.07** **(2016)**

13. Surajit Mondal, **Abhishek Sharma**, Vindhya Devalla, Sravendra Kumar Rana, Suresh Kumar, Jitendra Kumar Pandey, "An overview of cleaning and prevention processes for enhancing efficiency of solar photovoltaic panels", Current science (SCI-indexed)**, Impact Factor- 1** **(2017)**

14. Vikas Thapa, **Abhishek Sharma**, Beena Gairola, Amit Kumar Mondal, Vindhya Devalla, Ravi Kumar Patel, "A Review on Visual Odometry Techniques for Mobile Robots: Types and Challenges", Recent Advances in Electrical & Electronic Engineering, (Scopus-Indexed). **(2017)**

15. Venkateswaran Pedinti Sankaran, Santosh Dubey, **Abhishek Sharma**, Ajay Agarwal, Sanket Goel, "Stereolithographic 3D Printed Microfluidic Viscometer for Rapid Detection of Automobile Fuel Adulteration", Sensor Letters (Scopus-Indexed). **(2017)**

16. Rupendra Pachauri, **Abhishek Sharma***, Shailendra Rajput, "Parametric Effects on Proton Exchange Membrane Fuel Cell Performance: An Analytical Perspective, International Journal of Mathematical, Engineering and Management Sciences (ESCI-Indexed). **(2017)**

17. **Abhishek Sharma**, Abhinav Sharma, Sachi Choudhary, Rupendra Kumar Pachauri, Aayush Shrivastava, Deepak Kumar Pandey, "A Review On Artificial Bee Colony And It's Engineering Applications", Journal of critical reviews (Scopus-Indexed). **(2020)**

18. **Abhishek Sharma**, Rupendra Pachauri, Abhinav Sharma, Nikhil Raj, "Extraction of the solar PV module parameters using chicken swarm optimization technique", WITCON ECE-2019, IEEE conference, (International Conference). **(2020)**

19. Cris Thomas, Rahul Bharadwaj, Amit Mondal, **Abhishek Sharma**, Vindhya Devalla, "Design and Development of Voice Control System for Micro Unmanned Aerial Vehicles", AIAA-2018, Atlanta, Georgia (International Conference). **(2018)**

20. AK Mondal, RK Patel, **Abhishek Sharma**, V Devalla, S Mondal, "Comparative Analysis of Floating Aerogenerators", ICNEW-2017, India. (International Conference). **(2017)**

21. A Yadav, V Kaundal, **Abhishek Sharma**, P Sharma, D Kumar, P Badoni, "Wireless Sensor Network Based Patient Health Monitoring and Tracking System", ICICCD-2017, India. (International Conference). **(2017)**

22. PS Venkateswaran, V Kaundal, AK Mondal, **Abhishek Sharma**, V Devalla, "Air Mouse: An Everyday Mouse for the Ease of Computing", ICICCD-2017, India. (International Conference).**(2017)**

23. **Abhishek Sharma**, RK Patel, V Thapa, B Gairola, B Pandey, "Investigation on optimized relative localization of a mobile robot using regression analysis", Robotics: Current Trends and Future Challenges (RCTFC)-2016, India. (International Conference). **(2017)**

24. Venkateswaran, P.S., **Abhishek Sharma**, Ajay Agarwal and Sanket Goel, "3D Printed Lab-on-a-chip Microviscometer for various Biochemical Applications", 15th IEEE International Conference on Environment and Electrical Engineering, Rome-Italy. 2015. (International Conference). **(2015)**

BOOKS (AUTHORED/EDITED)

1. **Abhishek Sharma**, Abhinav Sharma, Jitendra Kumar Pandey, and Mangey Ram, "Swarm Intelligence: Foundation, Principles, and Engineering Applications", MEMS series, Taylor & Francis group, CRC Press. (Authored book, under publication process). **(2021)**

2. Rupendra Kumar Pachauri, Jitendra Kumar Pandey, **Abhishek Sharma**, Om Prakash Nautiyal, and Mangey Ram, "Applied Soft Computing and Embedded System Applications in Solar Energy", MEMS series, Taylor & Francis group, CRC Press. ISBN 9780367625122, 2021 **(2020)**

BOOK CHAPTERS

1. Abhinav Sharma, **Abhishek Sharma**, Vinay Chowdary, Aayush Srivastava, Puneet Joshi, "Cuckoo Search Algorithm: A Review of Recent Variants and Engineering Applications", Metaheuristic and Evolutionary Computation: Algorithms and Applications, pp 177-194, Springer. **(2019)**

2. Vinay Chowdary, Vivek Kaundal, Amit Kumar Mondal, Vindhya Devella, **Abhishek Sharma**, "Internet of things-enabled virtual environment for U-health monitoring", Sensors for Health Monitoring, 117-133, Academic Press. **(2019)**

Awards

1. Sandwich Fellowship-**2021** by Council of Higher Education (CHE), Israel.

2. Emerging Scientist Award by VDGood Platform, Hyderabad, **2021**.

Guest Lectures

1. Invited as a guest lecture on "Embedded Systems" in Aligarh Muslim University, India. **(2019)**

Certifications

1. Certified in "Innovation Management" by Erasmus University Rotterdam offered through online learning platform Coursera. **(2020)**

TRAININGS & PROJECTS UNDERTAKEN

M.Tech Final Major Project **Duration: 6 months**
Project Title: Multi-terrain remotely operated military vehicle with differential axle.
Description: Designed a U.G.V for defense purposes which would be able to target and could be controlled from 500m distance with video feedback.
Courses: Microprocessor and Microcontroller Programming (B+), Control Systems (B+), Wireless Sensor Network (B+), CAD/CAM (B), Analog and Digital Electronics (B), Master thesis (A-).

Summer Internship Project (During M. Tech) **Duration: 8 weeks**
Organization: University of Petroleum and Energy Studies
Project title: Work Space Mapping through Laser Range Finder**.**
Description: Designed a System to map the whole area for pine leaf collecting robot with the help of Laser Range Finder module interfaced with Atmega16 platform.

Organization: THINK LAB Pvt. Ltd. (During B. Tech) **Duration: 4 weeks**
Project Title: Embedded system
Description: The objective of the project was to develop the real-time applications.

RESEARCH INTERESTS

1. Multi-Agent systems and Dynamic Stability of Multi Robot.
2. Multi-terrain robot with Autonomous Navigation and Path Planning.
3. Swarm optimization of Multi Robot.
4. Wireless sensor Network.
5. Solar energy /Hybrid energy
6. Designing and fabrication of robotic parts using 3D Printer.

Research Guidance

1. Mr. Pranjal Paul, "Autonomous warehouse robot for 3D mapping using Kinect RGB-D camera", MTech, 2020 (completed).

ACADEMIC / EXTRA CURRICULAR ACHIEVEMENTS

- ✓ **Reviewer** of IEEE International Conference on Environment and Electrical Engineering, FLORENCE, ITALY, continuously **since last three Years**.
- ✓ Participated for Young Scientist Award in UCOST at State level.
- ✓ Actively participated and completed projects in Robotics workshop.
- ✓ Worked as a good Coordinator in Annual Function at my B. Tech Level.
- ✓ Won two times ROBORACE in the inter college competition.
- ✓ Participated in social activities.

REFEREES

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