PARAMETER ESTIMATION OF SOLAR PHOTOVOLTAIC CELL AND PROTON EXCHANGE MEMBRANE FUEL CELL USING HYBRID PARTICLE SWARM OPTIMIZATION DINGO OPTIMIZER ALGORITHM

A Dissertation submitted in fulfillment of the requirements for the Degree
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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, **"Parameter Estimation of Solar Photovoltaic Cell and Proton Exchange Membrane Fuel Cell using Hybrid Particle Swarm Optimization Dingo Optimizer Algorithm"**, in partial fulfillment of the requirements for the award of the degree of **Master of Engineering in Power Systems**, submitted to Electrical & Instrumentation Engineering Department of Thapar Institute of Engineering & Technology (Deemed to be University) is as authentic record of my own work carried under the supervision of **Dr. Parag Nijhawan**. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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LIST OF ABBREVIATIONS

Acronyms	Full form
PV	Photovoltaic
PEMFC	Proton Exchange Membrane Fuel Cells
STC	Standard Temperature Condition
SD	Standard Deviation
HPSODOX	Hybrid Particle Swarm Optimization and Dingo Optimizer
RMSE	Root Mean Square Error
SSE	Sum of Square Error
PSO	Particle Swarm Optimization
DOX	Dingo Optimizer
GWO	Grey Wolf Optimization
CS	Cuckoo Search
GWOCS	Grey Wolf optimizer and Cuckoo Search
PSOGWO	Particle Swarm Optimization and Grey Wolf Optimizer
MVO	Multi-Verse Optimizer
ALO	Ant Lion Optimizer
SCA	Sine Cosine Algorithm
MFO	Moth-Flame Optimization
SMA	Slime Mould Algorithm
GSA	Gravitational Search Algorithm
FPSO	Flexible Particle Swarm Optimization
SOS	Symbiotic Organisms Search
ABSO	Artificial Bee Swarm Optimization
MAE	Mean Absolute Error
ISCA	Enhanced Sine Cosine Algorithm
NMs	Nelder-Mead simplex
OBL	Opposition-based learning
HS	Harmony Search
SSA	Salp Swarm Algorithm
I-GWO	Improved Grey Wolf Optimizer
WHO	Wild Horse Optimizer
CLPSO	Closed-Loop Particle Swarm Optimization
EHO	Elephant Herd Optimization
MCSSC	Multi-Crystalline Silicon Solar Cells
BWO	Black Widow Optimization
SM	Slime Mould
HHO	Harris Hawks’ Optimization
ASO	Atom Search Optimization
EIA-PSO	Effective Informed Adaptive PSO
GA	Genetic Algorithms
HGA	Hybrid Genetic Algorithm

CS-EO	Cuckoo Search Algorithm with explosion operator

NOMENCLATURE

Notation	Description
I_{ph}	Photocurrent
R_{sh}	Shunt resistance
R_{se}	Series resistance
n	Ideality factor
I_o	Output current
$I_{dc1}, I_{dc2}, I_{dc3}, I_{dc4}$	Diode currents of four diodes
I_{sh}	Current through shunt resistor
$I_{rsd1}, I_{rsd2}, I_{rsd3}, I_{rsd4}$	Reverse saturation currents of four diodes
V_O	Output voltage
q	Electrical charge
T	Absolute temperature of P-N junction
K	Boltzmann’s constant
V_c	Terminal voltage of fuel cell
E_{Nernst}	Reversible open circuit voltage
$V_{\text{activation}}$	Activation voltage drop
V_{ohmic}	Ohmic voltage drop
$V_{\text{concentration}}$	Concentration voltage drop
T_c	Temperature of cell (in Kelvin)
P_{anode}	Pressure at anode
$P_{cathode}$	Relative humidity of vapour around the anode
α	Transfer coefficient
$\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4$	Semi-empirical coefficients on the cathode side of the fuel cell
R_{CR}	Resistance of the contact
R_{MR}	Membrane resistance
ρ_M	Membrane resistivity
λ	Adjustable empirical variable
b	Constant
n	Number of cells connected in series
V_i	Output voltage predicted
V_{actual}	Experimental output voltage
N	Number of measured data
x	Solution vector
c_1 and c_2	Acceleration parameter
w	Inertial weight vector
$\vec{A}$ and $\vec{B}$	Coefficient vectors
$\overrightarrow{a_1}$ and $\overrightarrow{a_2}$	Random vectors

ABSTRACT

In the recent few years, renewable energy sources have gained a lot of attention due to depletion of fossil fuels, increasing demand of energy as well as due to various advantages of renewable energy sources such as availability, cleanliness and reliability. Solar energy and Proton Exchange Membrane Fuel Cells (PEMFC) are most effective and promising sources of renewable energy. Hence, the effective and precise parameter estimation of solar photovoltaic (PV) cells and PEMFC is extremely crucial for precise evaluation, control of PV systems as well as simulation and development of highly efficient fuel cells. In this work, a new hybrid (HPSODOX) algorithm based on two widely used meta-heuristic algorithms that is, Particle Swarm Optimization (PSO) and Dingo Optimizer (DOX) is developed for parameter estimation of four diode model, modified four diode model of solar PV cell under different operating conditions and PEMFC. On comparison with other well-known meta-heuristic algorithms, the results obtained show that the developed hybrid (HPSODOX) algorithm has better performance in terms of accuracy, precision and efficiency.

Keywords: Four diode model, Modified four diode model, Proton exchange membrane fuel cell, HPSODOX, Parameter estimation, Meta-heuristic algorithms.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Due to increase in energy demand and depletion of fossil fuels along with various disadvantages such as air pollution, global warming, ozone depletion etc., [1] the world has shifted its attention towards renewable and inexhaustible energy sources for the clean energy in order to make the world a better place for living [2]. Some of the renewable energy sources constitute wind energy, solar energy, gravitational energy, hydropower, geothermal energy, biomass energy etc., [1] and have seen a significant development in the recent decades. Due to this, there has been a significant attraction in the attention for evaluation and control of renewable energy sources. Solar energy is considered as one of the most effective and promising renewable energy sources among all. Electrical energy is converted to Solar Energy through photovoltaic (PV) technology [3-4]. The behavior of non-linear I-V characteristics has been described by various mathematical models, and it is very essential to develop suitable methods for the evaluation of model parameters based on calculated data [5]. Therefore, the problem of parameter estimation can be defined as an optimization problem. Deterministic and Meta-heuristic methods are two different techniques for solution to optimization problems [6]. With a similar initial starting point, a deterministic algorithm dependably produces the same answer for a given issue. This behavior, however, leads to local optima entrapment, which is a drawback of deterministic optimization strategies. Local optima stagnation occurs when an algorithm becomes entrapped in local solutions, resulting in inability to locate the genuine global optimum. Because real-world issues contain a high number of local solutions, deterministic algorithms fail to locate the global optimum. Meta-heuristic algorithms, on the other hand have many advantages over deterministic algorithms such as flexibility, simplicity, less mathematical complexity and local optima avoidance. Meta-heuristic algorithms are inspired by nature such as animal behavior for the accomplishment of some task and yield satisfactory results for most of the complex problems. Meta-heuristic algorithms are very appropriate in order to find local optima in comparison to other conventional algorithms as the starting of optimization solution is with random processes and have the benefit of derivation-free mechanism as they optimize the problems stochastically.

With randomization comes a good way to move from local search to global search [7-8]. Despite having many advantages of meta-heuristic algorithms, it is still a challenge for finding global optima in case of optimization problems.

As solar energy is one of the practical and promising sources of renewable energy, parameter estimation of solar PV cell is an optimization problem in order to make the system more efficient and reliable. Meta-heuristic algorithms can be used for optimal parameter estimation of solar PV cell.

Fuel cells are integral part of sustainable energy sources having wide range of uses as well as rapid expansion like other renewable energy sources such as solar and wind energy. In fuel cell, chemical energy is transformed into electrical energy under controlled conditions. Most commonly used fuel cell is Proton Exchange Membrane Fuel Cell (PEMFC). Various meta-heuristic algorithms can be used to estimate the parameters of PEMFC.

1.2 LITERATURE REVIEW

1.2.1 Literature review on Meta-heuristic algorithms

Kennedy and Eberhart [9] discovered evolutionary optimization algorithm, Particle Swarm Optimization (PSO) inspired by the behavior of fish schooling, bird flocking as well as theory of swarming and its discovery was done by simulating a simplified social model which further moves to optimization. The developed algorithm is very simple, robust and effective for optimization of huge range of functions.

Mirjalili *et al.* [10] developed Grey Wolf Optimizer (GWO), a new meta-heuristic algorithm based on grey wolves. It is inspired by the hierarchy in leadership and mechanism of hunting followed by grey wolves. Hunting, finding the prey, prey encircling and attacking are the main steps implemented by four types of grey wolves i.e., alpha, beta, delta and omega. The results reveal that the developed algorithm delivers extremely competitive outcomes when compared with other meta-heuristic algorithms and presents a real-world application in various areas. Mirjalili *et al.* [11] devised a nature-inspired algorithm, Multi-Verse Optimizer (MVO) inspired by cosmology concepts i.e., white hole, black hole, and wormhole and further, to accomplish exploration, exploitation, and local search, mathematical models of these three concepts have been developed. The mathematical models developed are applied to real-world engineering problems for evaluation of performance of the proposed technique and the results reveal that this algorithm outperforms other optimization algorithms.

Mirjalili [7] proposed Ant Lion Optimizer (ALO), a novel nature-inspired algorithm based on the hunting of antlions. The five key processes of hunting prey include arbitrary movement of ants, the construction of traps, capture of ants in traps, the capture of preys and rebuilding of traps. The findings show that the proposed algorithm performs better in terms of exploration, local optima avoidance, exploitation, and convergence as well as solution to constrained problems can be achieved with a wide range of search spaces.

Mirjalili [12] developed Sine Cosine Algorithm (SCA), a unique population-based optimization algorithm. With the help of sine and cosine functions, a mathematical model is developed which is used to generate numerous initial random candidate solutions that should have fluctuation outwards or towards the optimal solution. This method also includes a number of random and adaptive variables that favor exploration and exploitation of the search space at certain optimization milestones. Test functions and performance metrics show that the proposed method can successfully explore various areas of a search space, local optima avoidance, convergence towards global optimum, and exploitation of potential areas of search space.

Yang and Deb [13] formulated Cuckoo Search (CS), a new meta-heuristic algorithm for optimization problems that is based on some cuckoo species' obligatory brood parasite behavior, as well as the Levy flying behavior of birds and fruit flies. The validation of the proposed algorithm against different test functions and its comparison with other well-known optimization algorithms reveal the superiority of CS in case of multimodal objective functions as well as the new algorithm is more generic and robust.

Amit *et al.* [8] presented Dingo Optimizer (DOX), a new meta-heuristic algorithm based on the behavior of dingo. Dingo is a type of dog whose scientific name is Canis Lupus and dingoes are complex, intelligent, very social and collaborative animals as well as skillful hunters. Hunting behavior of dingoes is the basis of the proposed algorithm including exploration, encircling and exploitation. Mathematical modelling of the steps for hunting of prey is done and applied in order to analyze the performance of the newly presented algorithm and the results illustrate that this algorithm outperforms other meta-heuristic algorithms in terms of best optimal solution and computational time.

Mirjalili [14] developed Moth-Flame Optimization (MFO) algorithm, a unique nature-inspired optimization algorithm. The major source of inspiration for this algorithm is the transverse orientation navigation approach used by moths in nature. This technique uses a mathematical model to optimize the flying behavior of moths at night by keeping a steady angle with the moon and also, these insects are caught in a deadly spiral path around the artificial lights during the journey. On comparison of the results with other optimization algorithms, it is observed that this algorithm gives promising results and has better and effective performance in real-world applications as well.

Shimin *et al.* [15] proposed a new optimization algorithm called Slime Mould Algorithm (SMA) which is inspired by the oscillation mode of slime mould. The proposed algorithm has numerous new features including a mathematical model in which adaptive weights are used for simulating the process of production of positive and negative feedback a slime mould propagation wave that is based on bio-oscillator for forming the best path in order to connect food with excellent exploration ability and exploitation propensity. While estimating the performance and efficiency of newly proposed algorithm, the results illustrate the competitive results when compared with other optimization algorithms.

Mirjalili and Hashim [16] proposed a new hybrid algorithm for optimization problems, PSOGA that is population-based. This algorithm is combination of two well-known optimization algorithms i.e., Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). The major concept behind this algorithm is to integrate the strengths of both the algorithms in order to obtain better results i.e., exploitation ability of PSO and exploration ability of GSA. Upon comparison with the individual optimization algorithms, the results reveal that proposed hybrid algorithm performs better in terms of function minimization, faster convergence and avoidance of local optimum.

Narinder and S. [17] presented HPSOGWO, a new hybrid nature-inspired algorithm that is based on Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO). The main objective of this paper is to combine the exploitation ability of Particle Swarm Optimization (PSO) with the exploration ability of Grey Wolf Optimizer (GWO) in order to develop better and more efficient algorithm. For performance evaluation of hybrid algorithm, unimodal, multimodal, and fixed-dimension multimodal test functions are used and the results demonstrate the better performance of HPSOGWO in terms of faster convergence, finding the global optimum and stable solution.

1.2.2 Literature review on parameter estimation of solar PV cell

Ebrahimi *et al.* [18] proposed Flexible Particle Swarm Optimization (FPSO) algorithm to estimate the parameters of solar PV cell. This algorithm adds an elimination phase to the traditional PSO algorithm, where, in the starting of every phase, deletion of some worst particles takes place and replacement of few new particles takes place in the new search space as well as the latter is changed on the basis of parameter values. These changes strengthen the proposed algorithm with addition of global search ability and space searching. Parameter estimation of single diode model, double diode model and PV module has been done using the proposed method and on comparison with other optimization algorithms, it is found that the proposed algorithm is more accurate and robust for parameter estimation of solar PV cell.

Xiong *et al.* [19] presented an application of Symbiotic Organisms Search (SOS) algorithm in order to do parameter estimation of solar PV cells. SOS, which was inspired by organisms' symbiotic interaction methods to increase their overall competitiveness in the environment, has several notable advantages, including the absence of algorithm-specific parameters to tune, a good balance between exploration and exploitation, and ease of implementation. The presented technique is validated using single diode model, double diode model and PV module model. The results reveal that the presented technique performs better than other well-known meta-heuristic algorithms in terms of accuracy, robustness, effectiveness and better convergence rate.

Askarzadeh and Rezazadeh [20] invented a new meta-heuristic algorithm based on the honey bees intelligent behavior of collecting and processing the nectar called as Artificial Bee Swarm Optimization (ABSO) for parameter estimation of solar PV cell using single diode and double diode models and R.T.C. France datasheet. A series of experimental results demonstrate the effective and efficient outcome of the proposed algorithm for parameter estimation of solar PV cell.

Ahmad *et al.* [21] presented a unique model for representing the I-V expression of traditional double diode model of PV cell. New parameters are defined and extraction of I-V curve is done by surpassing the traditional model as it is highly computational efficient. To evaluate the accuracy of presented technique, verification has been done at Standard Temperature Condition (STC) with the help of experimental parameters and outside STC by simulation and the findings reveal the better performance for recreation of I-V expression of solar PV cells.

Singla and Nijhawan [2] developed a new hybrid algorithm based on two well-known meta-heuristic algorithms i.e., Grey Wolf Optimizer (GWO) and Cuckoo Search (CS) algorithm in order to estimate the parameters of solar PV cell using triple diode model. A complete set of experimental results such as ranking test, analysis of statistical errors and temperature variation is carried out for determining the performance of the developed hybrid algorithm and the results reveal the promising and superior performance of hybrid algorithm in comparison to other optimization algorithms.

Vandana *et al.* [22] proposed a three diode model for industrial silicon solar cells and further parameter estimation of three diode model using evolutionary optimization algorithm i.e., Particle Swarm Optimization (PSO) algorithm. Estimated parameters with proposed three diode model are compared with parameters estimated by double diode model and the evaluation of Mean Absolute Error (MAE) reveal the accurate and precise estimation of parameters of solar PV cell using three diode model.

Huiling *et al.* [23] proposed a new enhanced Sine Cosine Algorithm (ISCA) on the basis of exploration and exploitation of Sine Cosine Algorithm (SCA) and further enhancement is done using Nelder-Mead simplex (NMs) and opposition-based learning (OBL) scheme as it intensifies the population and boosts the exploitation ability as well as the population is diversified ensuring a steady balance. Parameter estimation of single diode model, double diode model and PV module is done using the proposed method and for demonstrating the usefulness of ISCA, various performance metrices are evaluated that show the promising and stable outcome of the proposed algorithm.

E. *et al.* [24] used Multi-Verse optimization (MVO) algorithm for estimating the parameters of solar PV cell using single diode model and further simulation of PV cells is done under different conditions and by varying the temperature. In order to evaluate the performance of MVO, estimated parameters are compared with actual experimental parameters and the values of standard deviation and variance illustrate the accuracy and robustness of MVO. Further comparison of MVO with other well-known meta-heuristic algorithms shows the effectiveness and efficiency of MVO over other algorithms.

Jyoti *et al.* [25] presented a new technique based on swarm intelligence i.e., Chaotic Chicken Swarm Optimization for parameter estimation of solar PV cell using three diode model. Feature of diversification in the presented method is improved with the help of chaotic maps. To demonstrate the performance of new method, extraction of I-V and P-V curves is done along with various non-parametric statistical tests such as Kruskal-Wallis test and rank-sum test of Wilcoxon and the results show the high accuracy and robustness of proposed method as well as fast convergence rate.

Beigi and Maroosi [26] proposed a new algorithm based on combination of local optimization method with firefly algorithm in order to estimate parameters of solar PV cells using single diode and double diode model. Firefly algorithm has good exploration ability but requires a local optimization method for improving the exploitation ability. The proposed algorithm has lowest value of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and relative error when compared to other meta-heuristic algorithms, thus illustrating the promising and competitive results for parameter estimation of solar PV cell.

Askarzadeh and Rezazadeh [27] presented Harmony Search (HS) based methods for parameter estimation of solar PV cell using single diode and double diode model. Some of the advantages of HS are simple, easy to implement and high performance. Root Mean Square Error (RMSE) criterion is used in order to evaluate the difference between experimental values and model values along with Mean Absolute Error (MAE) and relative error and the values of these performance metrices illustrate the more accuracy and precision of the presented method, thereby proving it to be a capable and efficient algorithm in order to estimate the parameters of solar PV cell.

Ramzi [28] used a new meta-heuristic algorithm known as Salp Swarm Algorithm (SSA) for parameter estimation of solar PV cell using single diode and double diode model having three steps i.e., retrieval of parameters in traditional method, determination of uncertainty of every parameter and determining the parameters by taking in account the earlier two steps. In order to validate the effectiveness of SSA, a series of experimental as well as statistical test is done and on comparing it with other well-known optimization algorithms, it is found that SSA outperforms other algorithms in terms of stability, robustness and accuracy.

Abd-ElHady *et al.* [29] presented a new algorithm i.e., Improved Grey Wolf Optimizer (I-GWO) for estimating the parameters of solar PV cell using three diode model. Advantages of I-GWO over GWO include improvement in population, steady balance between exploration and exploitation abilities and faster rate of convergence. The presented algorithm is applied to two datasheets i.e., R.T.C. France and PTW and performance metrices taken are Root Mean Square Error (RMSE), current absolute error and statistical analysis. On evaluation, it is revealed that I-GWO has least value of RMSE and other performance metrices as compared to other meta-heuristic algorithms, thus proving it to be more accurate, precise, efficient and robust algorithm for parameter estimation of solar PV cell.

Abdelhady *et al.* [30] proposed a new optimization algorithm i.e., Wild Horse Optimizer (WHO) for parameter estimation of solar PV cell using double diode model, modified double diode model, triple diode model and modified triple diode model. The basis of WHO is the social organization behavior of horses including grazing, hierarchy followed in leadership, dominance etc. It is also focused on original as well as modification of the models as modifying the original model by adding a series resistance with one of the diodes improves the efficiency of the original model. Performance metrices used for evaluation are Root Mean Square Error (RMSE) and analysis of statistics in order to check accuracy and robustness respectively. On carrying out a comprehensive analysis, it is revealed that WHO performs better and satisfactory for parameter estimation of solar PV cell. Further, the findings show that modified double diode model and modified triple diode models are more accurate than the original models of solar PV cells.

Ahmed *et al.* [31] devised two new meta-heuristic algorithms i.e., Closed-Loop Particle Swarm Optimization (CLPSO) and Elephant Herd Optimization (EHO) for parameter estimation of modified triple diode model of solar PV cell. Multi-Crystalline Silicon Solar Cells (MCSSC) have been used in this proposed method and the technique is applied on experimental data under different levels of temperature and radiance. On evaluation, it is found that proposed method has lowest value of RMSE and faster rate of convergence. The results also reveal that modified triple diode model has more accuracy and precision as compared to modified double diode model at low value of illumination, thus proving it to be a superior method for parameter estimation of solar PV cells.

1.2.3 Literature review on parameter estimation of Proton Exchange Membrane fuel cell (PEMFC)

Manish *et al.* [32] introduced a new meta-heuristic algorithm called as Black Widow Optimization (BWO) for estimating the parameters of PEMFC. The proposed method is first benchmarked on functions for validation and then used to estimate the parameters of PEMFC at different temperature conditions, and the results obtained are further compared with other well-known meta-heuristic algorithms. Two datasheets i.e., Ballard Mark V and Avista SR-12 are used. A complete set of statistical analysis is carried out for analyzing the performance of the proposed method and the results reveal that BWO has significantly better, effective and efficient performance with faster convergence rate for PEMFC parameter estimation.

Jyoti *et al.* [33] proposed a new optimization algorithm based on Slime Mould (SM) in order to estimate the parameters of PEMFC. SM is inspired by the fungus. The results of the complex benchmark test functions illustrate the promising output of the proposed algorithm along with the lowest values of mean and standard deviation than other algorithms, thus proving it to be more accurate. Further, convergence graph and I-V, P-V characteristic curves give more justification to the accuracy of SM. For evaluation of the performance, non-parametric statistical tests are performed which illustrate that SM performs better than other optimization algorithms in terms of accuracy, precision and faster convergence.

Mahmoud *et al.* [34] introduced two new meta-heuristic algorithms i.e., Harris Hawks' Optimization (HHO) and Atom Search Optimization (ASO). HHO is inspired by the analysis of birds' population behavior, whereas the basis of ASO is the combination of physics and swarm-based characteristics in order to find the global optima. The proposed technique is applied on various stacks of PEMFC at different conditions of operation. Value of Sum of Square Errors (SSE) has been calculated in order to analyze the performance of the new method. The proposed algorithm performs better than all other algorithms in terms of accuracy, effectiveness, efficiency, and fast speed of convergence.

Massimo *et al.* [35] presented a new technique based on stochastic optimization for parameter estimation of PEMFC under different operating conditions i.e., temperature, pressure and humidity. Stochastic Optimization methods have advantage of escaping local minima and the findings show the better performance of stochastic optimization techniques in terms of accuracy and less computational time.

Meiying *et al.* [36] used an evolutionary optimization algorithm i.e., PSO for parameter estimation of PEMFC in terms of V-I characteristic curves. Using PSO, the simulation has been done that includes noisy and noise-free. On estimating the PEMFC parameters, it is found that satisfactory and promising outcome can be achieved even in case of noisy simulation data. After obtaining V-I characteristic curves, it is shown that PSO has significantly better and efficient performance when compared to other optimization algorithms.

Fathy and Rezk [37] applied Multi-verse Optimizer (MVO) in order to find optimal parameters of PEMFC at different operating conditions. MVO is based on the theory of multi universes in which collision and interaction takes place and the major idea behind this is the white holes, black holes and worm holes. Polarization curve obtained using MVO is converged to the experimental. Comparison of results obtained using MVO with other well-known optimization algorithm demonstrate the outperformance of proposed algorithm in terms of simplicity, accuracy, efficiency, effectiveness, reliability, less computational and convergence time.

Qi *et al.* [38] improved the well-known optimization algorithm i.e., PSO and presented Effective Informed Adaptive PSO (EIA-PSO) algorithm for parameter estimation of PEMFC having steady balance between local and global search. On comparing the values of simulation with experimental data, it is found that EIA-PSO has significantly better performance than other algorithms in terms of accuracy, precision, robustness and less CPU time. The proposed algorithm also has better global and local search ability as well as search rate.

Mohamed and Jenkins [39] estimated the model parameters of PEMFC using genetic algorithms (GA). GA is inspired by the natural biological evolution and generates a huge set of solutions possible to a problem and on evaluation, fitness level near to the optimal solution is decided and includes crossover and mutation. Evaluation of average fitness of 20 solutions is done and further presented polarization curve. On comparing the results of simulation with experimental data, it is found that GA gives promising competitive results.

Zhi-Jun *et al.* [40] introduced a new optimization algorithm i.e., Hybrid Genetic Algorithm (HGA) for parameter estimation of PEMFC. In the proposed algorithm, Nelder-Mead’s simplex method is merged into Genetic Algorithms (GA) for maintaining the diversity of population in order to prevent premature convergence as well as improves the local search ability. The solution can be made more accurate by increasing the number of individuals and maximum number of evolution generations. Comparison of results obtained as well as I-V characteristic curve reveal the reliable, robust, accurate, effective and steady-state performance of HGA.

Chen and Wang [41] a new algorithm i.e., Cuckoo Search Algorithm with explosion operator (CS-EO) for parameter estimation of PEMFC. In CS-EO, search ability is improved with the help of adaptive strategy of step size and local minima is avoided. CS-EO is first benchmarked on test functions for validation and it is found that it is more accurate and has better convergence. CS algorithm is based on the parasitic behavior of cuckoo species. Parameter estimation results of CS-EO on comparison with other meta-heuristic algorithms illustrate the outperformance of the proposed algorithm in terms of efficiency, accuracy, effectiveness and robustness.

M. *et al.* [42] devised a new meta-heuristic algorithm known as Grey Wolf Optimizer (GWO) for parameter estimation of PEMFC. GWO is based on the behavior of grey wolves and includes exploration and exploitation in order to perform better. Sum of Square Error (SSE) has been used as performance matrix and GWO has lowest value of SSE. Further, parametric and non-parametric statistical tests are also carried out and the findings reveal that GWO has better, reliable, effective and robust performance when compared to other well-known meta-heuristic algorithms.

1.3 RESEARCH GAPS

On the basis of detailed study of literature, identification of following research gaps is done:

1. Various optimization and meta-heuristic algorithms have been studied in depth and applied in wide range of areas in different research works. Further, hybrid algorithms consisting of nature-inspired algorithms can be developed and explored on various applications for better and improved results.
2. In the literature review, it is observed that maximum research work is done on single diode, double diode and triple diode model of solar PV cell, whereas no research work is done on four diode and modified four diode model of solar PV cell.

1.4 OBJECTIVES OF RESEARCH WORK

On the detailed review of literature and identification of research gaps, the objectives of research work are as follows:

1. Development of new hybrid algorithm based on nature-inspired algorithms.
2. Parameter estimation of four diode and modified four diode model of solar PV cell using various meta-heuristic and hybrid algorithm.
3. Parameter estimation of PEMFC using various meta-heuristic and hybrid algorithm.

1.5 THESIS CONTRIBUTION

The main contribution of thesis is as follows:

1. New hybrid meta-heuristic algorithm, HPSODOX, based on two well-known nature-inspired algorithms i.e., Particle Swarm Optimization (PSO) and Dingo Optimizer (DOX) has been developed.
2. Parameter estimation of four diode, modified four diode model of solar PV cell and PEMFC has been done using the developed hybrid algorithm as well as other well-known meta-heuristic algorithms.
3. The developed hybrid algorithm is benchmarked on test functions and calculation of mean and standard deviation (SD) is done in order to validate the hybrid algorithm.

4. Value of Root Mean Square Error (RMSE) and Sum of Square Error (SSE) has been calculated for solar PV cell and PEMFC respectively. The values obtained are compared for evaluation of performance of developed hybrid algorithm. Non-parametric test is also carried out to justify the superior performance of HPSODOX against the compared algorithms.

1.6 THESIS ORGANIZATION

This thesis consists of following chapters:

CHAPTER 1 represents the deep study of renewable energy sources such as solar energy and fuel cells as well as its advantages over conventional energy sources. Further, comprehensive overview of various optimization techniques and meta-heuristic algorithms as well as their application in various areas is discussed in this chapter. Detailed literature review on parameter estimation of solar PV cells and PEMFC is presented. Afterwards, research gap as well as objectives are listed. At the end, Thesis contribution and organization is mentioned.

CHAPTER 2 consists of detailed description of mathematical modelling of four diode and modified four diode model of solar photovoltaic (PV) cell and Proton Exchange Membrane Fuel Cell (PEMFC).

CHAPTER 3 comprises of parameter estimation of solar PV cell and PEMFC. A detailed description of meta-heuristic algorithms is given along with problem formulation and objective function of solar PV cell and PEMFC.

CHAPTER 4 consists of results and discussion of parameter estimation of solar PV cell and PEMFC.

CHAPTER 5 consists of conclusion and future scope of work.

CHAPTER 2

MODELLING OF SOLAR PHOTOVOLTAIC CELL AND PROTON EXCHANGE MEMBRANE FUEL CELL (PEMFC)

2.1 INTRODUCTION

Due to depleting fossil fuels and increasing energy demand, renewable energy resources are a promising alternative to exhaustible and non-renewable energy resources. The major and practical source of renewable energy is Solar energy as it is available in abundance, has high efficiency and low maintenance cost. The recent few years have seen a tremendous increase in the solar power technology as it can be used in diverse applications such as solar water heating, solar pumping, solar distillation, solar heating of buildings, solar furnaces etc. Silicon semiconductor based photovoltaic (PV) generators generate electric current. Output of the highly non-linear system, photovoltaic (PV) generator is power and voltage which varies with change in the environment such as temperature variation and the irradiances [1]. So, appropriate optimization technique is needed to improve the overall efficiency and reliability of PV systems by obtaining the suitable values of parameters such as diode ideality factor (n), series and shunt resistance i.e., R_{se} and R_{sh} respectively, reverse saturation current (I_{rsd}) and photocurrent (I_{ph}). As observed from the literature review that most of the research work on solar PV cells is done by considering single diode model, double diode model and triple diode model, whereas no research work is done by considering four diode model of solar PV cell. However, these models are more efficient and accurate than the basic single diode model. Therefore, by using these advanced models of solar PV cells, a better and efficient algorithm can be developed to estimate the parameters with more accuracy and precision.

Fuel cell is one of major source of renewable energy sources having number of advantages such as reliability, cleanliness, and steady power generation. Fuel cells have a wide range of uses and have expanded rapidly, much like the most prevalent renewable energy sources (wind and solar), making them a powerful competitor [33] as well as having applications in car manufacturing and heating firms. The operation of fuel cell is based on chemical reaction that takes place under controlled conditions [34] and the chemical energy is transformed into electrical energy. The major components of a fuel cell are anode and a cathode having an electrolyte between them.

Depending on the type of electrolyte used, several kinds of fuel cells can be designed, one of which is Proton Exchange Membrane Fuel Cell (PEMFC). Because of the high-power density at low temperatures and quick responsiveness to electro-dynamic processes, PEMFC has attracted a lot of attention. PEMFC is durable, stable, energy efficient and environment friendly resource of energy. Furthermore, its widespread characteristics expand its application in a range of fields, such as military, generation of power, backup of power supply, etc. [43]. As the structure of fuel cells has thin layers formed of various materials, analysis of their behavior and necessitate complete characterization of these materials which includes determining physical, electrical, thermal and chemical properties. Due to significance of PEMFC and its progress in the use of industrial applications, it has become important to design and develop a more accurate and precise model in order to understand the processes occurring in the fuel cell, thus saving time as well as effort. Many attempts have been made to develop better models for identification of the functions of PEMFC. There is huge significance of modelling characteristics of PEMFC in study, simulation and development of high performance and efficient fuel cells. The datasheet of any PEMFC does not contain sufficient statistics for finding optimal set of parameters. There are considerable differences between the data acquired from the model and that given in the manufacturer's datasheet. Therefore, parameter estimation of PEMFC can be considered as an optimization problem and different algorithms can be used to obtain the optimal set of solution to this problem.

2.2 MATHEMATICAL MODELLING OF PHOTOVOLTAIC CELLS

2.2.1 Four Diode Model

Four diode model is the improved version of Three diode model in which an additional diode i.e., fourth diode is connected in parallel to the third diode and rest of the circuit is same. Figure 2.1 represents the equivalent circuit of four diode model. This model has numerous advantages when compared to single, double and triple diode models such as more accuracy in case of industrial solar PV cells, minimum error between the experimental and calculated data, high curve fitting accuracy than other models and good performance under Standard Temperature Condition (STC). This model is used for parameter estimation in case of big industrial applications where size is more than 155.2 cm^2 and 17.1% efficiency and I_{dc1}, I_{dc2} and I_{dc3} estimated values are not sufficient for representation of different parameters of solar PV cell.

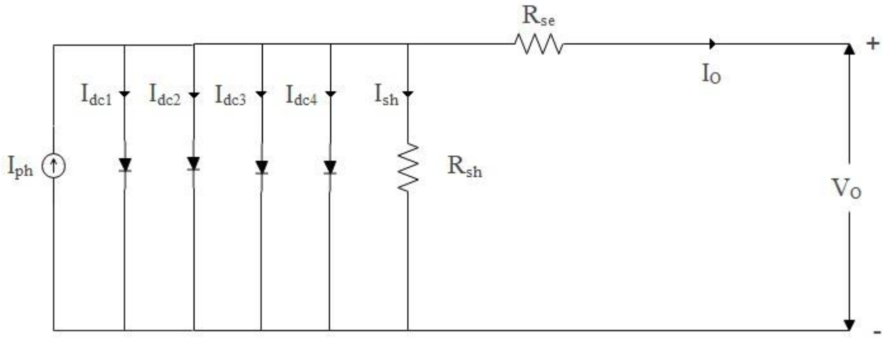


Figure 2.1: Schematic equivalent circuit model of four diode solar PV cell

As shown in the above figure, four diode model of solar PV cell consists of four diodes, a current source, a series and shunt resistor i.e., R_{se} and R_{sh} respectively. The basis of this model is the diffusion and recombination of the diode current with n as the non-physical diode ideality factor. The output current, I_o can be represented as:

$$I_o = I_{ph} - I_{dc1} - I_{dc2} - I_{dc3} - I_{dc4} - I_{sh} \tag{2.1}$$

where

I_{ph}	Photocurrent
$I_{dc1}, I_{dc2}, I_{dc3}, I_{dc4}$	Diode currents of four diodes
I_{sh}	Current through shunt resistor, R_{sh}

Further, diode currents can be written as follows:

$$I_{dc1} = I_{rsd1}\left\lfloor exp\left(\frac{q(V_O+I_O R_{se})}{n_1 KT}\right) - 1\right\rfloor \tag{2.2}$$

$$I_{dc2} = I_{rsd2}\left\lfloor exp\left(\frac{q(V_O+I_O R_{se})}{n_2 KT}\right) - 1\right\rfloor \tag{2.3}$$

$$I_{dc3} = I_{rsd3}\left\lfloor exp\left(\frac{q(V_O+I_O R_{se})}{n_3 KT}\right) - 1\right\rfloor \tag{2.4}$$

$$I_{dc4} = I_{rsd4}\left\lfloor exp\left(\frac{q(V_O+I_O R_{se})}{n_4 KT}\right) - 1\right\rfloor \tag{2.5}$$

where

$I_{rsd1}, I_{rsd2}, I_{rsd3}, I_{rsd4}$	Reverse saturation currents of four diodes
V_O	Output voltage
q	Electrical charge i.e., $1.602 \times 10^{-19}\ (C)$
T	Absolute temperature of P-N junction (in Kelvin)
K	Boltzmann's constant i.e, $1.381 \times 10^{-23}\ (J/K)$

Now, the output current, I_o can be represented as:

$$I_O = I_{ph} - I_{rsd1}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_1KT}\right)-1\right] - I_{rsd2}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_2KT}\right)-1\right] - I_{rsd3}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_3KT}\right)-1\right] - I_{rsd4}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_4KT}\right)-1\right] - \frac{V_O+I_OR_{se}}{R_{sh}} \tag{2.6}$$

2.2.2 Modified Four Diode Model

Various diode-based PV models are Single diode model, Double diode model, Triple diode model, and Four diode model. Four diode model of PV cell consists of four diodes which are connected with two resistors, one in series and other in parallel, thus total of eleven parameters are formed. Modelling in four diode type model can be improved with addition of a series resistance (R_4) with one diode in order to represent the quasi-neutral region losses as shown in Figure 2.2.

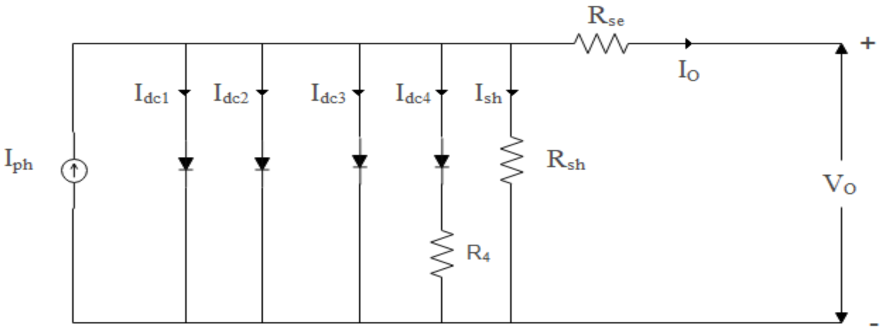


Figure 2.2: Schematic equivalent circuit model of modified four diode solar PV cell

Following equation represents the modelling of modified four diode model of solar PV cell.

$$I_O = I_{ph} - I_{rsd1}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_1KT}\right)-1\right] - I_{rsd2}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_2KT}\right)-1\right] - I_{rsd3}\left[exp\left(\frac{q(V_O+I_OR_{se})}{n_3KT}\right)-1\right] - I_{rsd4}\left[exp\left(\frac{q(V_O+I_OR_{se}-I_{rsd4}R_4)}{n_4KT}\right)-1\right] - \frac{V_O+I_OR_{se}}{R_{sh}} \tag{2.7}$$

2.3 MATHEMATICAL MODELLING OF PEMFC

PEMFC contains two electrodes i.e., cathode and anode separated by polymer electrolyte membrane as shown in Figure 2.3. The electrolyte is made up of thin membrane that is capable of conducting ions and prevents electrons from passing through it. The anode is injecting hydrogen and the cathode is injecting oxygen. The activation energy produced by the hydrogen oxidation is decreased by the catalysts. The ions flow through the electrolyte, while the electrons pass through the outside circuit, resulting in generation of output voltage.

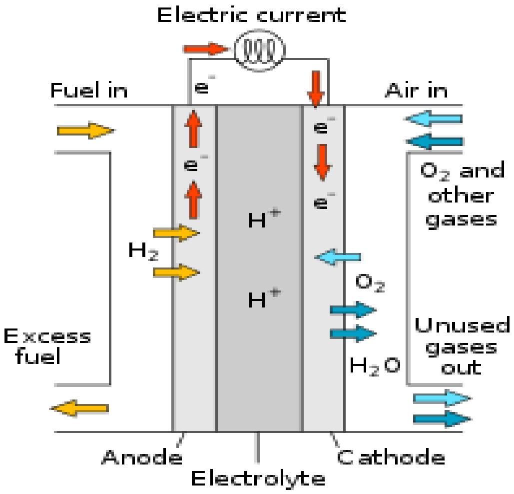


Figure 2.3: Diagram of PEMFC

The following equations represent the electrochemical reactions that occur in the electrodes of the PEMFC.

$$H_2 \rightarrow 2H^+ + 2_e^- \tag{2.8}$$

$$\frac{1}{2}O_2 + 2H^+ + 2_e^- \rightarrow H_2O \tag{2.9}$$

$$H_2 + \frac{1}{2}O_2 \rightarrow H_2O \tag{2.10}$$

The equation (2.8) and (2.9) shows the chemical reaction at anode side and cathode side respectively. The total chemical reaction in cell is shown in equation (2.10) and it also refers the generation of electrical energy.

$$V_c = E_{\text{Nernst}} - V_{\text{activation}} - V_{\text{ohmic}} - V_{\text{concentration}} \tag{2.11}$$

Terminal voltage of fuel cell (V_c) mainly constitutes three types of voltage and is represented in equation (2.11), where, E_{Nernst} is the reversible open circuit voltage, $V_{\text{activation}}$ is the activation voltage drop, V_{ohmic} is the ohmic voltage drop, $V_{\text{concentration}}$ is the concentration voltage drop.

$$E_{\text{Nernst}} = E_r + \frac{RT_c}{ZF}\left[\ln\left(P_{H_2}\right) + \ln\left(\sqrt{P_{O_2}}\right)\right] \tag{2.12}$$

Equation (2.12) represents the Nernst equation in which reversible thermodynamic potential of oxygen and hydrogen reaction is defined, where E_r is the reference voltage, R is the universal gas constant, T_c is the temperature of cell (in Kelvin), z represents the number of electrons transferred, F is the faraday constant,$P_{H_2}$and P_{O_2} represent the hydrogen and oxygen pressure respectively. Further, equation (2.12) can be re-written as following after expanding.

$$E_{\text{Nernst}} = 1.229 - 8.5 \times 10^{-4}(T_c - 298.15) + 4.385 \times 10^{-5}T_c \times \left(\ln\left(P_{H_2}\right) + \ln\left(\sqrt{P_{O_2}}\right)\right) \tag{2.13}$$

$$P_{H_2} = 0.5\left(PH_{anode} \times P_{H_2O}\right)\left[\left(exp\left(\frac{1.635\left(\frac{i_c}{A}\right)}{{T_c}^{1.334}}\right) \times \frac{\left(PH_{anode} \times P_{H_2O}\right)}{P_{anode}}\right)^{-1} - 1\right] \tag{2.14}$$

$$P_{O_2} = \left(PH_{cathode} \times P_{H_2O}\right)\left[\left(exp\left(\frac{4.192\left(\frac{i_c}{A}\right)}{{T_c}^{1.334}}\right) \times \frac{\left(PH_{anode} \times P_{H_2O}\right)}{P_{cathode}}\right)^{-1} - 1\right] \tag{2.15}$$

P_{H_2} and P_{O_2} are represented by equations (2.14) and (2.15) respectively, where P_{anode} and $P_{cathode}$ denotes the pressure at anode and cathode respectively of the input side, PH_{anode} and $PH_{cathode}$ represent the relative humidity of vapour around the anode and cathode side of the fuel cell respectively, i_c is the current which is generated by the fuel cell, A represents the surface area of the membrane, P_{H_2O} represents the pressure at water saturation, which is further illustrated in equation (2.16).

$$P_{H_2O} = 2.95 \times 10^{-2}(T_c - 273.15) - 9.18 \times 10^{-5}(T_c - 273.15)^2 + 1.44 \times 10^{-2}(T_c - 273.15)^2 - 2.18 \tag{2.16}$$

$$V_{\text{activation}} = \frac{RT_c}{z\alpha F}\ln\left(\frac{i_c}{i_O}\right) \tag{2.17}$$

Equation (2.17) represents the loss in voltage due to activation process, where α the transfer coefficient is and i_O is the exchange current density. This equation can further be extended as follows.

$$V_{\text{activation}} = -\left[\varepsilon_1 + \varepsilon_2 T_c + \varepsilon_3 T_c \ln\left(C_{O_2}\right) + \varepsilon_4 T_c \ln(i_c)\right] \tag{2.18}$$

Where $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4$ are the semi-empirical coefficients on the cathode side of the fuel cell. Equation (2.19) calculates the concentration of oxygen (C_{O_2}).

$$C_{O_2} = \frac{P_{O_2}}{5.08\times 10^6 exp^{\left(\frac{-498}{T_c}\right)}} \tag{2.19}$$

The resistive ohmic voltage drop (V_{ohmic}) is shown in equation (2.20), where R_{MR} is the surface resistance of the membrane, and R_{CR} is the resistance of the contact.

$$V_{\text{ohmic}} = i_c(R_{MR} + R_{CR}) \tag{2.20}$$

$$R_{MR} = \frac{\rho_M l}{A} \tag{2.21}$$

Equation (2.21) calculates the membrane resistance (R_{MR}), where ρ_M is the membrane resistivity and l is the membrane thickness. Further, ρ_M can be expressed as follows.

$$\rho_M = \frac{181.6\left(1+0.03\left(\frac{i_c}{A}\right)+0.0062\left(\frac{T_c}{303}\right)\left(\frac{i_c}{A}\right)^{2.5}\right)}{\left(\lambda-0.634-3\left(\frac{i_c}{A}\right)\right) exp\left(418\left(\frac{T_c-303}{T_c}\right)\right)} \tag{2.22}$$

Where λ denotes the adjustable empirical variable. Equation (2.23) calculates the value of voltage concentration loss ($V_{\text{concentration}}$).

$$V_{\text{concentration}} = \frac{RT_c}{z\alpha F} \ln\left(\frac{i_d}{i_d - i_c}\right) \tag{2.23}$$

Where i_d represents the current density in case of zero reactant concentration. Equation can further be re-written as follows.

$$V_{\text{concentration}} = -b \ln\left(i_c - \frac{\frac{i_c}{A}}{i_{max}}\right) \tag{2.24}$$

Where b is the constant and i_{max} is the maximum current density. The value of b can be calculated as per equation (2.25).

$$b = \frac{RT_c}{z\alpha F} \tag{2.25}$$

Electrical energy generation is depicted in equation (2.10) that takes place by electrons supply to cathode side through electrical load circuit at anode side of the fuel cell. Since the output voltage and current of a single stack of PEMFC is very small, there is need to combine and connect multiple stacks in series or parallel for the generation of sufficient energy. In case of series connection, the output voltage (V_{stack}) of the stack of the fuel cell is represented in equation (2.26).

$$V_{stack} = n.V_c \tag{2.26}$$

Where n is the number of cells connected in series. Equation (2.26) can further be re-written as follows.

$$V_{stack} = n(E_{\text{Nernst}} - V_{\text{activation}} - V_{\text{ohmic}} - V_{\text{concentration}}) \tag{2.27}$$

For parameter estimation of PEMFC, as per above mentioned equations, seven parameters are to be estimated accurately. Usually, the datasheet of manufacturer does not contain some of the parameters. It is very important to do accurate and precise parameter estimation of PEMFC for adequate modelling and controlled operation of fuel cell. Seven unknown parameters of PEMFC i.e., $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \lambda, R_{CR}, b$ are to be estimated.

CHAPTER 3

PARAMETER ESTIMATION OF SOLAR PHOTOVOLTAIC CELL AND PROTON EXCHANGE MEMBRANE FUEL CELL (PEMFC)

3.1 INTRODUCTION

Conventional methods and meta-heuristic algorithms are two optimization strategies for parameter estimation of Solar PV Cell and PEMFC. Due to highly non-linear characteristics of Solar PV Cell and PEMFC parameters, conventional optimization techniques are less precise and accurate, whereas parameter estimation of Solar PV Cell and PEMFC with meta-heuristic algorithms comes with numerous advantages such as global optimal solution convergence, random initial guess and solution to complex problems. Hence, various strategies have been developed over the last few years in order to estimate the parameters of Solar PV Cell and PEMFC starting with conventional methods to meta-heuristic optimization algorithms. In this study, parameter estimation of Solar PV Cell and PEMFC has been done using the proposed hybrid algorithm, HPSODOX as well as other meta-heuristic algorithms i.e., PSO, GWO, GWOCS, DOX, PSOGWO. Further, comparison of HPSODOX has been done with other meta-heuristic algorithms in order to evaluate its efficiency.

3.2 PROBLEM FORMULATION AND OBJECTIVE FUNCTION

3.2.1 Solar Photovoltaic Cell

3.2.1.1 Problem Formulation

Optimization technique helps in identification of the unknown parameters and the real system set of experimental I-V data. Vector x defines the solution obtained by the optimization algorithm where $x = [R_{se}\ R_{sh} I_{ph} I_{rsd1} I_{rsd2} I_{rsd3} I_{rsd4} n_1 n_2 n_3 n_4]$ in the four diode model of solar PV cell, whereas in case of modified four diode model, the value of vector x is $x = [R_{se} R_{sh} R_4 I_{ph} I_{rsd1} I_{rsd2} I_{rsd3} I_{rsd4} n_1 n_2 n_3 n_4]$. The main objective of parameter estimation of solar PV cell is to minimize the error between measured currents and calculated currents. Equation (2.6) and (2.7) can be rewritten in homogeneous form as equation (3.14) and (3.15) respectively to define the objective function, and for the experimental data, value of f is calculated for four diode and modified four diode model of solar PV cell.

$$f(V_O, I_O, x) = I_O - I_{ph} + I_{rsd1}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_1KT}\right) - 1\right\rfloor + I_{rsd2}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_2KT}\right) - 1\right\rfloor + I_{rsd3}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_3KT}\right) - 1\right\rfloor + I_{rsd4}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_4KT}\right) - 1\right\rfloor + \frac{V_O+I_OR_{se}}{R_{sh}} \tag{3.14}$$

$$f(V_O, I_O, x) = I_O - I_{ph} + I_{rsd1}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_1KT}\right) - 1\right\rfloor + I_{rsd2}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_2KT}\right) - 1\right\rfloor + I_{rsd3}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se})}{n_3KT}\right) - 1\right\rfloor + I_{rsd4}\left\lfloor exp\left(\frac{q(V_O+I_OR_{se}-I_{rsd4}R_4)}{n_4KT}\right) - 1\right\rfloor + \frac{V_O+I_OR_{se}}{R_{sh}} \tag{3.15}$$

3.2.1.2 Objective Function

For every set of experimental data obtained, the value of f is calculated. In this study, Root Mean Square Error (RMSE) method is used to evaluate the difference between experimental data and model results. The main purpose of parameter estimation of solar PV cell is to minimize the difference between experimental data and model results. The value of RMSE is defined in equation (3.16).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f_i(V_O, I_O, x)\right)} \tag{3.16}$$

where N is the number of measured data, and x is the solution vector. The constraints are as following:

$$I_{pvmin} \le I_{pv} \le I_{pvmax}$$

$$I_{rsdmin} \le I_{rsd} \le I_{rsdmax} \quad \text{rsd=1:4}$$

$$R_{semin} \le R_{se} \le R_{semax}$$

$$R_{shmin} \le R_{sh} \le R_{shmax}$$

$$n_{imin} \le n_i \le n_{imax} \quad \text{i=1:4}$$

Therefore, the key objective of parameter estimation of solar PV cell is to minimize the value of RMSE.

3.2.2 Proton Exchange Membrane Fuel Cell (PEMFC)

3.2.2.1 Problem Formulation

Optimization algorithms help in finding optimal solution to the problem of parameter estimation of PEMFC. In this study, a new hybrid algorithm, HPSODOX is proposed for accurate and precise parameter estimation of PEMFC. Using the optimization algorithms, the output voltage is predicted against every current density input.

3.2.2.2 Objective Function

The evaluation metric between the predicted output voltage using optimization algorithms and experimental values of output voltage is Sum of square error (SSE). Equation (3.17) represents the objective function.

$$SSE = MIN(F = \sum_{i=1}^{N}(V_{actual} - V_i)^2) \tag{3.17}$$

Where N is the number of data points, V_{actual} represents the experimental output voltage and V_i represents the output voltage predicted using optimization algorithms. The constraints are as following:

$$\varepsilon_{nmin} \leq \varepsilon_n \leq \varepsilon_{nmax} \quad \text{n} = 1{:}\,4$$

$$\lambda_{min} \leq \lambda \leq \lambda_{max}$$

$$R_{CRmin} \leq R_{CR} \leq R_{CRmax}$$

$$b_{min} \leq b \leq b_{max}$$

The main objective of this work is to minimize the value of Sum of square error (SSE) in order to obtain better performance and more accurate and precise parameter estimation of PEMFC.

3.3 ALGORITHMS

3.3.1 Particle Swarm Optimization (PSO)

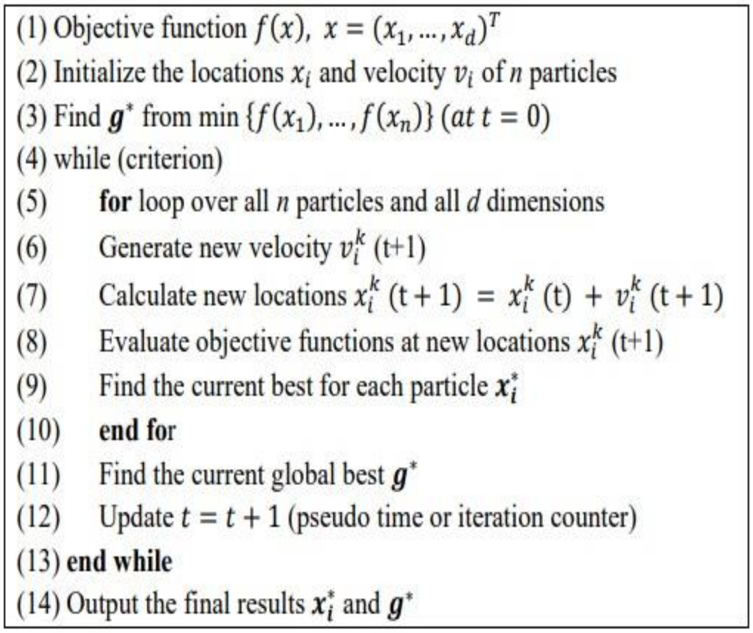
Developed in 1995, by J. Kennedy and R. C. Eberhard, Particle Swarm Optimization (PSO) is based on the behavior of bird flocking and fish schooling. When this algorithm is applied to any optimization problem (minimize or maximize the fitness function), initially, a number of random solutions are generated, where each solution is a particle (of the swarm) in the search space. Position and velocity of every particle is random. Afterwards, the optimal solution is found by swarm of particles by updating their own best solution and the best solution obtained by swarms. This is done by calculating fitness values corresponding to the fitness function for each iteration and obtaining two best fitness values i.e., pbest and gbest, where pbest is the best fitness value achieved by a particle and gbest is the best fitness value obtained by any particle in the population so far. The positions of the particles are changed with respect to the best particle's position. The equation (3.1), determines the new velocity vector:

$$v_i^k\ (t+1) = w \times v_i^k(t) + c_1 \times r_1 \times (pbest_i^k(t) - x_i^k(t)) + c_2 \times r_2 \times (gbest^k - x_i^k) \tag{3.1}$$

$$x_i^k\ (t+1) = x_i^k\ (t) + v_i^k\ (t+1) \tag{3.2}$$

where v_i^k (t+1) and x_i^k (t+1) represents velocity and position of ith particle in kth dimension at (t+1)th iteration, v_i^k (t) and x_i^k (t) is the velocity and position of ith particle in kth dimension at (t)th

iteration. r_1 and r_2 are the random numbers in the range [0,1], c_1 and c_2 represent the acceleration parameter and w represents the inertial weight vector for controlling the momentum of the particles. The current position of the ith particle in kth dimension is represented by $pbest_i^k$ and the best value of all the particles in kth dimension is represented by $gbest^k$. In equation (3.1), second term represents personal influence and the third term represents social influence. Particle's own experience is expressed by personal influence and collaboration among particles is expressed by social influence. The main objective of this algorithm is to change the position and velocity of every particle iteratively in order to achieve the overall best solution of the particle. Pseudo code and flow chart for Particle Swarm Optimization (PSO) are in shown in Figure 3.1 and Figure 3.2, respectively.



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Objective function $f(x),\ x = (x_1, \dots, x_d)^T$
Initialize the locations $x_i$ and velocity $v_i$ of $n$ particles
Find $\boldsymbol{g}^*$ from min $\{f(x_1), \dots, f(x_n)\}$ $(at\ t = 0)$
while (criterion)
    for loop over all $n$ particles and all $d$ dimensions
        Generate new velocity $v_i^k$ (t+1)
        Calculate new locations $x_i^k (t+1) = x_i^k (t) + v_i^k (t+1)$
        Evaluate objective functions at new locations $x_i^k$ (t+1)
        Find the current best for each particle $\boldsymbol{x}_i^*$
    end for
    Find the current global best $\boldsymbol{g}^*$
    Update $t = t + 1$ (pseudo time or iteration counter)
end while
Output the final results $\boldsymbol{x}_i^*$ and $\boldsymbol{g}^*$
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Figure 3.1: Pseudo code of Particle Swarm Optimization (PSO) Algorithm

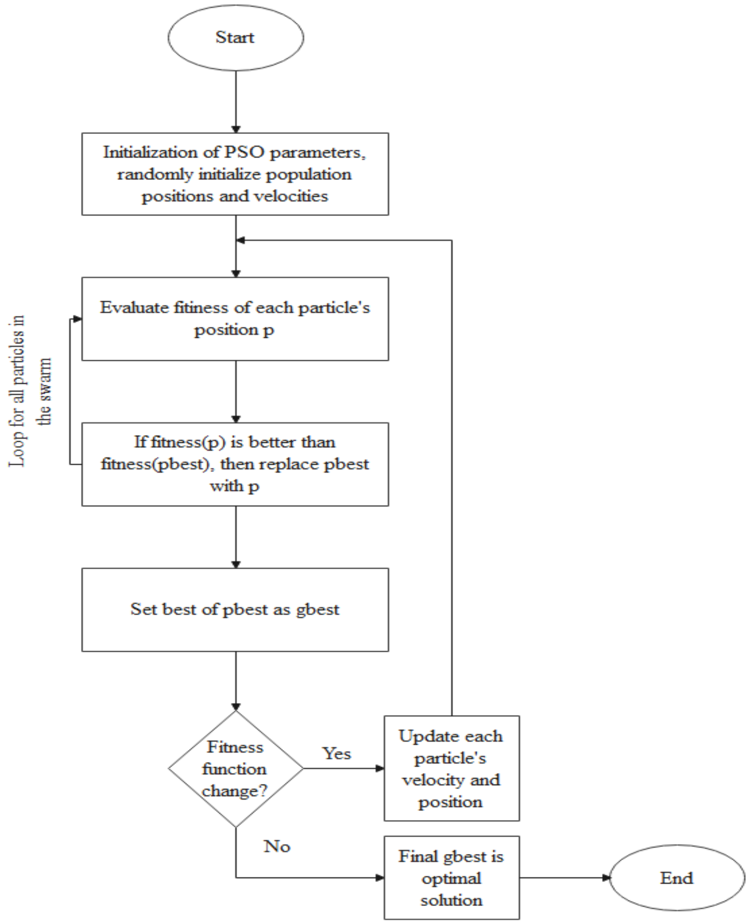


Figure 3.2: Flowchart of the Particle Swarm Optimization (PSO) Algorithm

3.3.2 Dingo Optimizer (DOX)

Dingo Optimizer (DOX) is inspired by the social and collaborative behavior of dingoes (Dingo is a type of dog whose scientific name is Canis Lupus). This algorithm takes into account the social hierarchy of dingoes and their prey hunting behavior. There are three main components of the hunting behavior of dingoes i.e., exploration, exploitation, and encircling. In the search space, various expected solutions are reached by the exploration component in the algorithm, whereas the exploitation component searches for the optimal solution. In order to find the best solution, there is requirement of both the components with fine balance over the search space.

Dingoes have the capability to trace the location of the prey, after which they encircle the prey. Following mathematical equations (3.3)- (3.7) model the behavior of the dingoes [8].

$$\overrightarrow{D_d} = \left|\vec{A} \cdot \overrightarrow{P_p}(x) - \vec{P}(i)\right| \tag{3.3}$$

$$\vec{P}(i+1) = \overrightarrow{P_p}(i) - \vec{B} \cdot \vec{D}(d) \tag{3.4}$$

$$\vec{A} = 2 \cdot \overrightarrow{a_1} \tag{3.5}$$

$$\vec{B} = 2\,\vec{b} \cdot\ \overrightarrow{a_2}\text{-}\vec{b} \tag{3.6}$$

$$\overrightarrow{b} = 3 - \left(I * (3/I_{maxiter})\right) \tag{3.7}$$

where $\overrightarrow{D_d}$ is distance between the dingo and prey, $\overrightarrow{P_p}(x)$is the position vector of prey, $\vec{P}(i)$ is the position vector of dingo, $\vec{A}$ and $\vec{B}$ are Coefficient vectors, $\overrightarrow{a_1}$ and $\overrightarrow{a_2}$ are random vectors in [0,1], $\overrightarrow{b}$ is Linearly decrement from 3 to 0 at every iteration, I is 1,2,3…….$I_{maxiter}I_{maxiter}$is maximum number of iterations.

Dingoes change their locations according to equations (3.3) and (3.4). All the other dingoes need to update their position after finding the location of the best search agent, which are modelled in following equations (3.8)- (3.13).

$$\overrightarrow{D_a} = \left|\overrightarrow{A_1} \cdot \overrightarrow{P_a} - \vec{P}\right| \tag{3.8}$$

$$\overrightarrow{D_b} = \left|\overrightarrow{A_2} \cdot \overrightarrow{P_b} - \vec{P}\right| \tag{3.9}$$

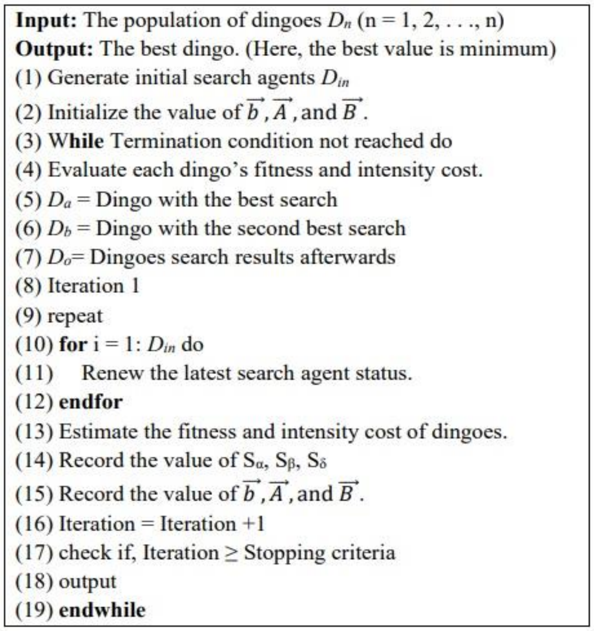
$$\overrightarrow{D_o} = \left|\overrightarrow{A_3} \cdot \overrightarrow{P_o} - \vec{P}\right| \tag{3.10}$$

$$\overrightarrow{P_1} = \left|\overrightarrow{P_a} - \overrightarrow{B} \cdot \overrightarrow{D_A}\right| \tag{3.11}$$

$$\overrightarrow{P_2} = \left|\overrightarrow{P_b} - \overrightarrow{B} \cdot \overrightarrow{D_b}\right| \tag{3.12}$$

$$\overrightarrow{P_3} = \left|\overrightarrow{P_1} - \overrightarrow{B} \cdot \overrightarrow{D_o}\right| \tag{3.13}$$

Pseudo code and flow chart for Dingo Optimizer (DOX) having stopping criteria as the maximum number of iterations are in shown in Figure 3.3 and Figure 3.4, respectively.



```
Input: The population of dingoes $D_n$ (n = 1, 2, . . ., n)
Output: The best dingo. (Here, the best value is minimum)
Generate initial search agents $D_{in}$
Initialize the value of $\vec{b}$, $\vec{A}$, and $\vec{B}$.
While Termination condition not reached do
Evaluate each dingo's fitness and intensity cost.
$D_a$ = Dingo with the best search
$D_b$ = Dingo with the second best search
$D_o$= Dingoes search results afterwards
Iteration 1
repeat
for i = 1: $D_{in}$ do
    Renew the latest search agent status.
endfor
Estimate the fitness and intensity cost of dingoes.
Record the value of $S_\alpha$, $S_\beta$, $S_\delta$
Record the value of $\vec{b}$, $\vec{A}$, and $\vec{B}$.
Iteration = Iteration +1
check if, Iteration $\geq$ Stopping criteria
output
endwhile
```

Figure 3.3: Pseudo Code of Dingo Optimizer (DOX) Algorithm

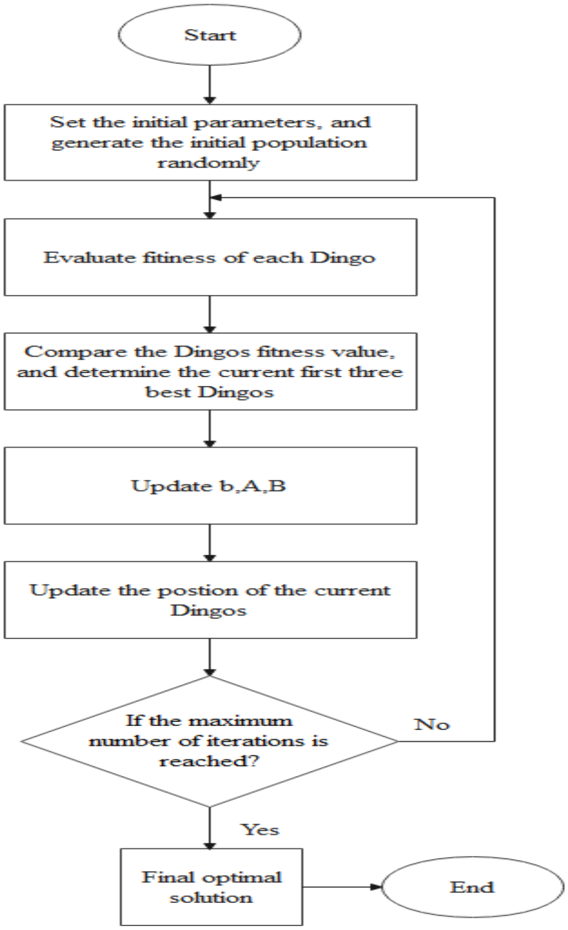
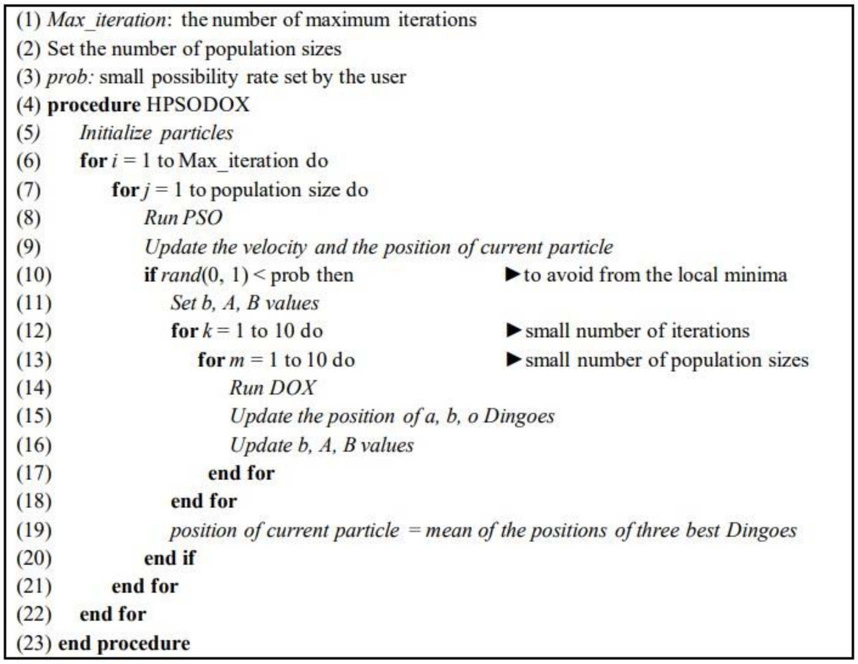


Figure 3.4: Flowchart of the Dingo Optimizer (DOX) Algorithm

3.3.3 Hybrid PSODOX (HPSODOX)

Parameter estimation of solar PV cell using meta-heuristic algorithms yields satisfactory results. However, these algorithms still have some disadvantages. For instance, convergence of Differential Evolution (DE) is not stable, and falls into a regional optimum easily. GA is easily trapped in premature convergence and is time consuming. Manual parameter setting is required in case of the Bee algorithm [44].

Particle Swarm Optimization (PSO) and Dingo Optimizer (DOX) are two distinct meta-heuristic algorithms with different search mechanism. PSO algorithm is inspired from the swarm behavior such as bird flocking, whereas DOX is inspired by the hunting behavior of dingoes. In most of the problems, PSO algorithm gives successful results. However, in PSO, there is partial optimism and solutions converge prematurely, thus losing the diversity of population [44]. In this work, a new method to estimate the parameters of solar PV cell is developed i.e., Hybrid PSODOX to obtain better results. Pseudo code and flow chart of new developed algorithm are shown in Figure 3.5 and Figure 3.6 respectively. The detailed results and discussion is given in the next chapter.



```
Max_iteration: the number of maximum iterations
Set the number of population sizes
prob: small possibility rate set by the user
procedure HPSODOX
    Initialize particles
    for i = 1 to Max_iteration do
        for j = 1 to population size do
            Run PSO
            Update the velocity and the position of current particle
            if rand(0, 1) < prob then                 ▶to avoid from the local minima
                Set b, A, B values
                for k = 1 to 10 do                    ▶small number of iterations
                    for m = 1 to 10 do                ▶small number of population sizes
                        Run DOX
                        Update the position of a, b, o Dingoes
                        Update b, A, B values
                    end for
                end for
                position of current particle = mean of the positions of three best Dingoes
            end if
        end for
    end for
end procedure
```

Figure 3.5: Pseudo Code of Hybrid PSODOX Algorithm

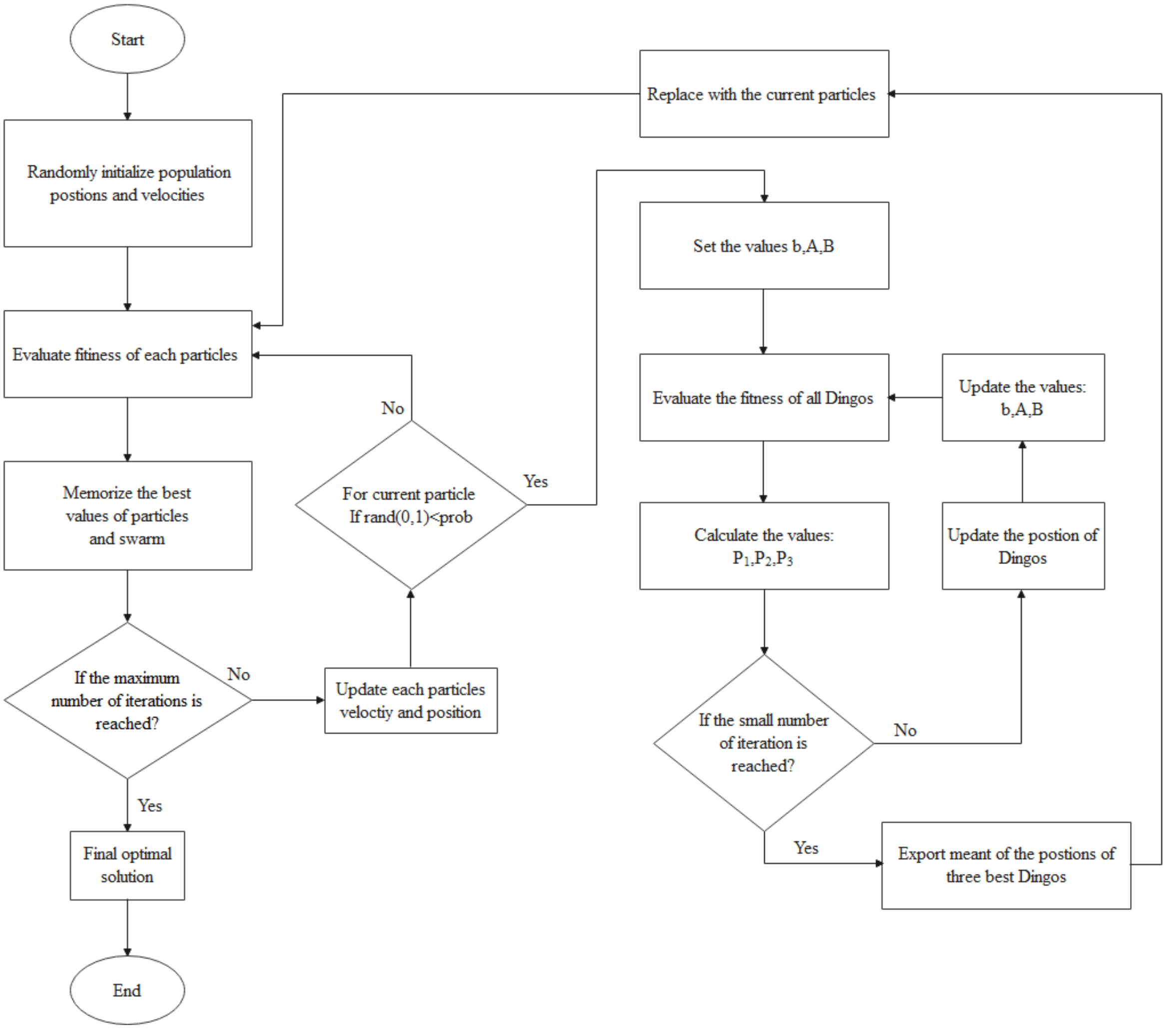


Figure 3.6: Flowchart of the HPSODOX Algorithm

CHAPTER 4

RESULTS AND DISCUSSION

4.1 INTRODUCTION

Parameter estimation of four diode, modified four diode model of solar PV cell and PEMFC has been done using developed hybrid meta-heuristic algorithm i.e., HPSODOX. The results obtained i.e., benchmark test functions, parameter estimation and non-parametric tests are discussed in this chapter.

4.2 FOUR DIODE MODEL OF SOLAR PV CELL

4.2.1 Benchmark Test Functions

The newly developed hybrid (HPSODOX) algorithm is benchmarked on chosen ten test functions for the validation of its efficiency. The characteristics of the benchmark test functions are presented in Table 4.1, where $F_1(k)$ to $F_7(k)$ are uni-modal functions and $F_8(k)$ to $F_{10}(k)$ are multi-modal functions, and the dimension of each function is set to 50. The performance of HPSODOX is further compared with three meta-heuristic algorithms i.e., PSO, GWO, DOX [5], and two hybrid algorithms i.e., GWOCS, PSOGWO. Coding of all programs is done in MATLAB 2020a and all algorithms are implemented in window 10 with 8 GB RAM and an intel CPU 2.50GHz processor. Each algorithm is independently run 20 times with same feature evaluations limit i.e., 1000 for comparing benchmark test functions for justification of superiority of the developed hybrid (HPSODOX) algorithm. Table 4.2 shows the mean and the values of standard deviation (SD) obtained by various algorithms on benchmark test functions. It is clearly observed from the results that the hybrid (HPSODOX) algorithm has better performance than other algorithms with better convergence rate, precision, and robustness. Figures 4.1 to 4.10 illustrate the bar graph of the value of the mean of 10 benchmark test functions using the proposed hybrid algorithm compared with PSO, GWO, DOX, GWOCS, and PSOGWO.

Table 4.1: Definitions of Benchmark Test Functions

Function	Dim	Range
$F_1(k) = \sum_{j=1}^{m} k_j^2$	50	[-100, 100]
$F_2(k) = \sum_{j=1}^{m} \lvert k \rvert + \prod_{j=1}^{m} \lvert x \rvert$	50	[-10, 10]
$F_3(k) = \sum_{j=1}^{m} \left(\sum_{j=1}^{m} k_j^2 \right)^2$	50	[-100, 100]
$F_4(k) = \max_j \lvert k_j \rvert, 1 \leq j \leq m$	50	[-100, 100]
$F_5(k) = \sum_{j=1}^{m-1} \left[100(k_{j+1} - k_j^2)^2 + (k_j - 1)^2 \right]$	50	[-30, 30]
$F_6(k) = \sum_{j=1}^{m} (\lvert k_j + 0.5 \rvert)^2$	50	[-100, 100]
$F_7(k) = \sum_{j=1}^{m} i k_j^4 + \text{random}[0,1]$	50	[-1.28, 1.28]
$F_8(k) = \sum_{j=1}^{m} -k_j \sin\left(\sqrt{\lvert k_j \rvert} \right)$	50	[-500, 500]
$F_9(k) = \sum_{j=1}^{m} \left[k_j^2 - 10\cos(2\pi k_j) + 10 \right]$	50	[-5.12, 5.12]
$F_{10}(k) = -20 \exp\left(-0.2 \sqrt{(1/m) \sum_{j=1}^{m} k_j} \right) - \exp\left((1/m) \sum_{j=1}^{m} \cos(2\pi k_j) + 20 + e \right)$	50	[-32, 32]

Table 4.2: Results of Benchmark Test Functions for Four Diode Model

Algorithms		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
PSO	Mean	2.43E+03	1.43E+01	4.11E+04	7.82E+01	1.26E+07	4.92E+03	3.53E+00	-1.13E+03	2.67E+02	1.23E+01
	SD	1.71E+03	2.52E+01	6.04E+03	9.93E+00	2.66E+07	1.04E+04	1.00E+01	1.49E+02	1.86E+01	4.51E+00
GWO	Mean	4.90E+01	6.62E+00	1.14E+04	8.49E+00	5.19E+06	2.69E+03	2.05E+00	-3.78E+03	9.88E+01	4.68E+00
	SD	1.55E+02	1.79E+00	1.61E+04	2.05E+01	3.42E+06	1.52E+03	1.06E+00	2.68E+02	9.69E+01	6.69E+00
DOX	Mean	9.28E-15	6.46E-10	8.79E+01	1.55E-03	2.71E+01	1.76E+00	4.16E-03	-4.33E+03	2.20E+00	1.37E-08
	SD	1.12E-14	4.22E-10	1.06E+02	1.00E-03	8.11E-01	2.59E-01	2.90E-03	2.52E+02	3.89E+00	1.17E-08

GWOCS	Mean	4.35E-15	6.71E-20	4.51E-09	1.98E-08	2.69E+01	1.39E+00	1.49E-03	-6.76E+03	1.43E+00	4.28E-14
	SD	1.38E-14	4.08E-20	5.95E-09	1.87E-08	2.48E-01	3.47E-01	6.87E-04	4.57E+02	4.52E+00	2.25E-15
PSOGWO	Mean	8.76E-35	2.59E-20	2.21E-09	6.33E-09	2.62E+01	3.62E-01	8.15E-04	-7.48E+03	8.53E-14	4.17E-14
	SD	8.97E-35	1.80E-20	3.57E-09	5.52E-09	3.81E-01	3.19E-01	2.15E-04	8.07E+02	1.24E-13	3.84E-15
HPSODOX	Mean	1.10E-70	1.48E-43	7.57E-136	1.29E-19	0.00E+00	2.71E-01	1.16E-04	-1.19E+04	6.35E-16	5.76E-15
	SD	3.46E-70	3.74E-43	2.20E-135	3.53E-19	0.00E+00	2.12E-01	7.72E-05	1.57E+03	1.52E-15	3.29E-14

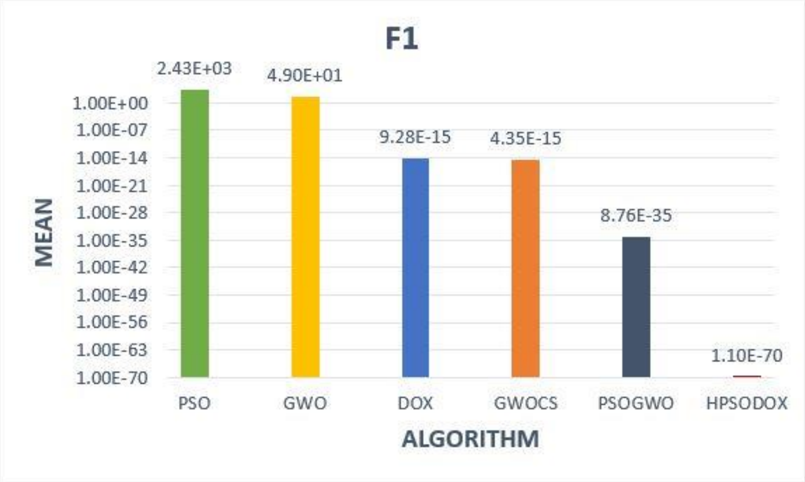


Figure 4.1: Bar graph of Benchmark Test Function, F1 for Four Diode Model

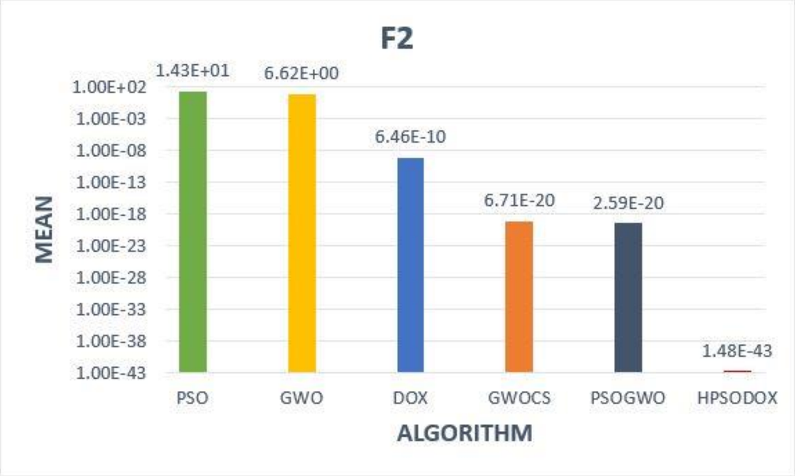


Figure 4.2: Bar graph of Benchmark Test Function, F2 for Four Diode Model

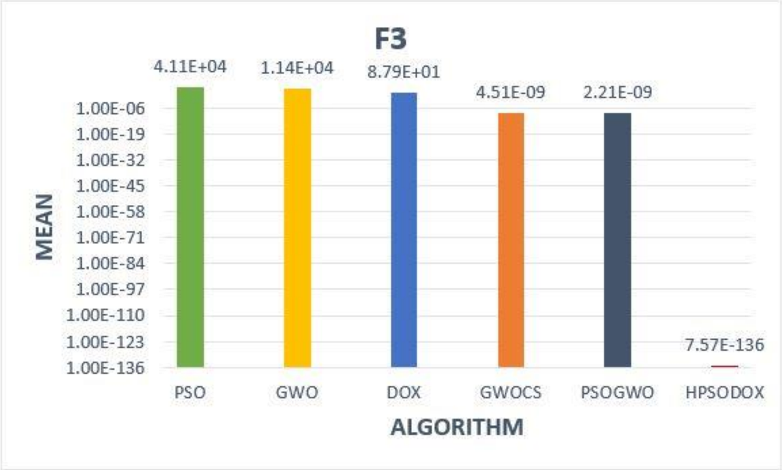


Figure 4.3: Bar graph of Benchmark Test Function, F3 for Four Diode Model

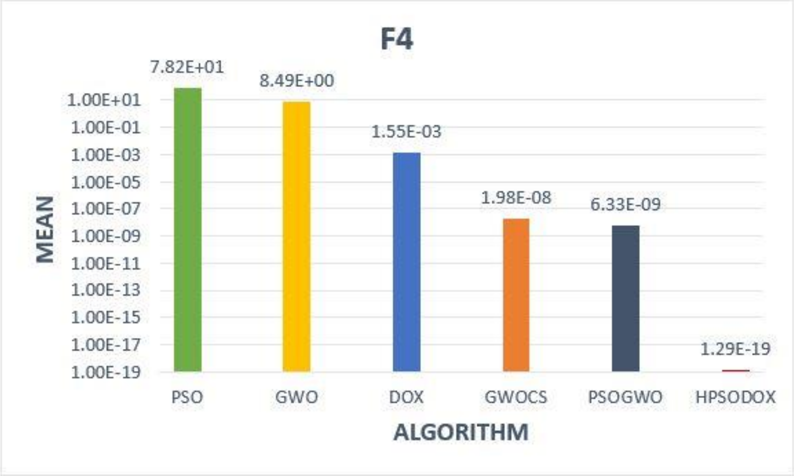


Figure 4.4: Bar graph of Benchmark Test Function, F4 for Four Diode Model

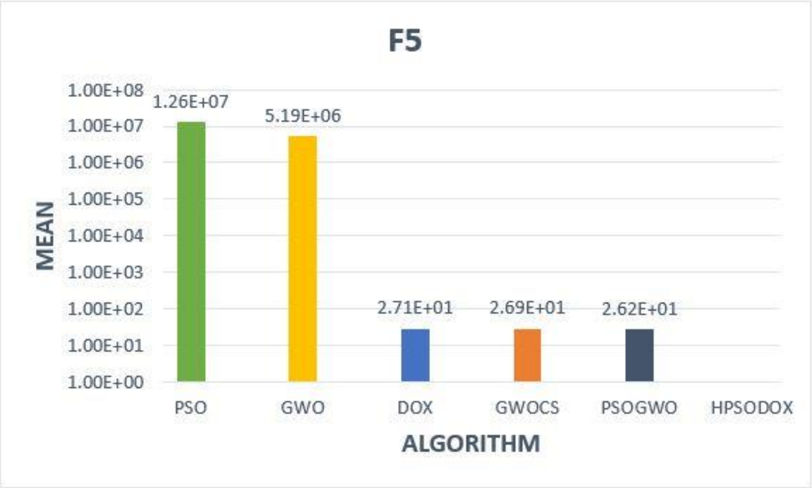


Figure 4.5: Bar graph of Benchmark Test Function, F5 for Four Diode Model

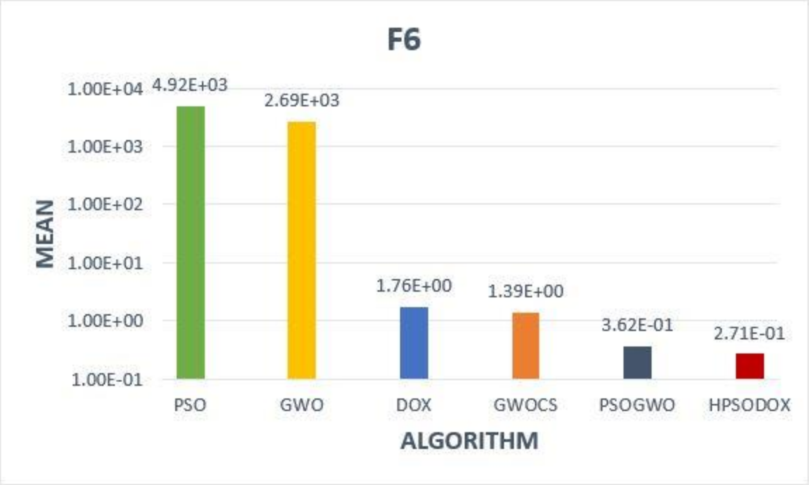


Figure 4.6: Bar graph of Benchmark Test Function, F6 for Four Diode Model

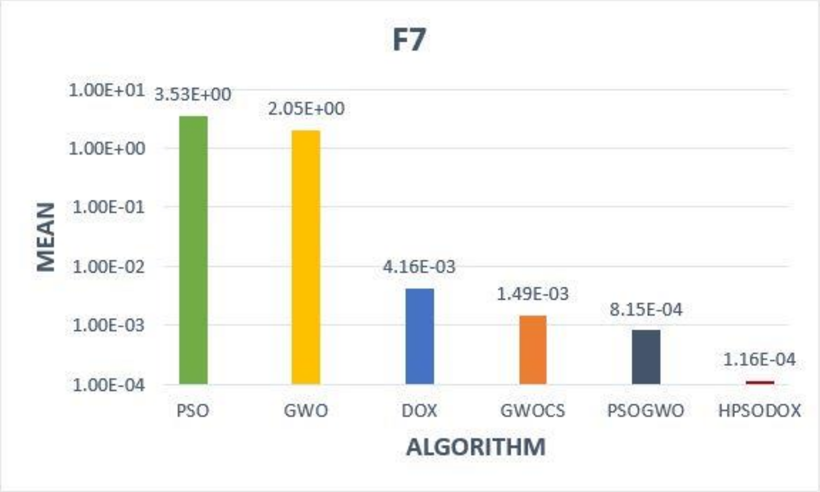


Figure 4.7: Bar graph of Benchmark Test Function, F7 for Four Diode Model

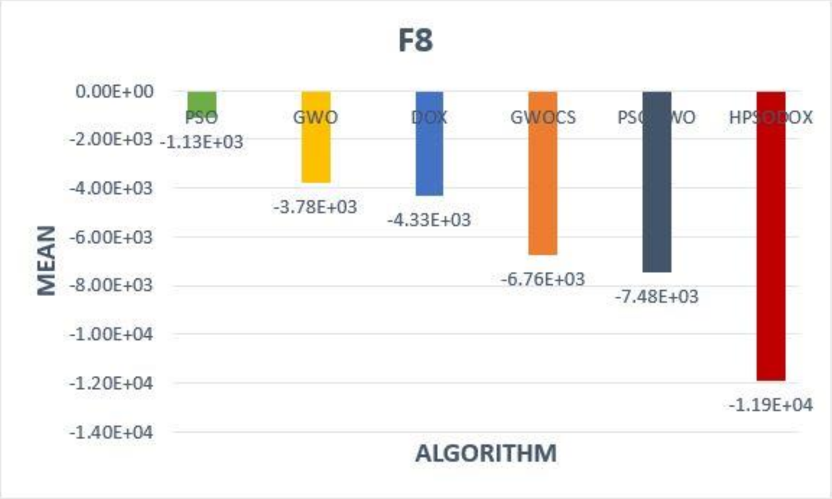


Figure 4.8: Bar graph of Benchmark Test Function, F8 for Four Diode Model

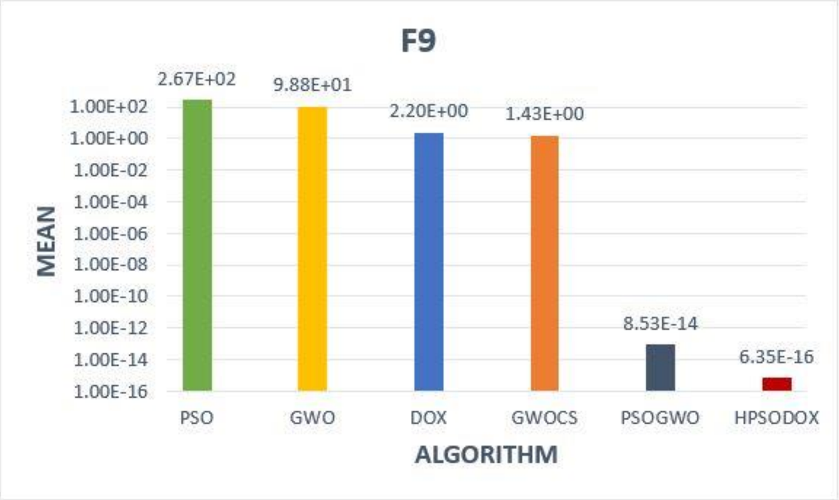


Figure 4.9: Bar graph of Benchmark Test Function, F9 for Four Diode Model

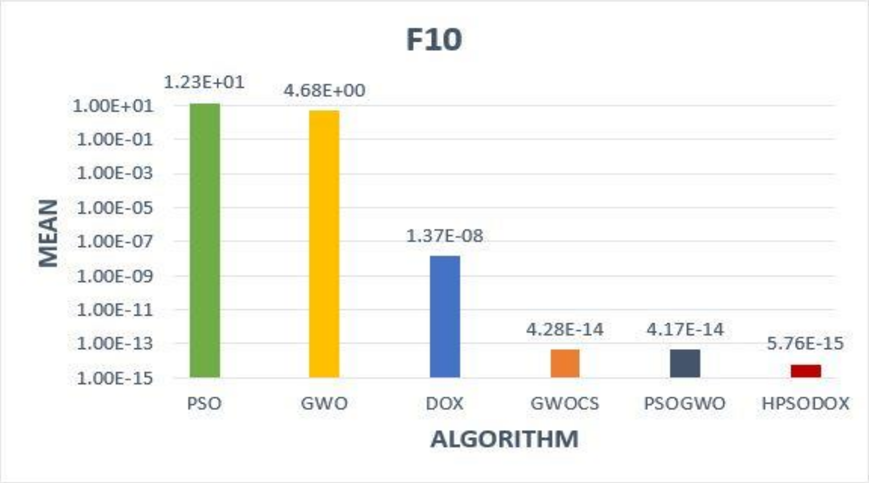


Figure 4.10: Bar graph of Benchmark Test Function, F10 for Four Diode Model

4.2.2 Parameter Estimation

In order to do parameter estimation of solar PV cell diode model, parameter search range is taken as shown in Table 4.3. Table 4.4 represents the data sheet of R.T.C. France for the same. After estimating the parameters of four diode model of solar PV cell using new developed hybrid (HPSODOX) algorithm, Root Mean Square Error (RMSE) is calculated, which is further compared with the other algorithms i.e., PSO, GWO, DOX, GWOCS, PSOGWO. Table 4.5 represents the four diode model parameter estimation and corresponding value of Root Mean Square Error (RMSE) which is calculated at standard temperature condition (STC). Bar graph of RMSE at STC is shown in Figure 4.11. Table 4.6 represents the four diode model temperature variation effect on the various estimated parameters using the algorithms considered in this work.

Computational time (sec) of HPSODOX is minimum as compared to other algorithms and its Bar Graph is shown in Figure 4.12.

Table 4.3: Parameter Search Range of solar PV cell models

Parameters	Lower bound	Upper bound
I_{pv}(A)	0	1
I_{rsd1},I_{rsd2},I_{rsd3},I_{rsd4} (μA)	0	1
R_{se}(Ω)	0	0.5
R_{sh}(Ω)	0	100
n_1,n_2,n_3,n_4	1	2

Table 4.4: Data sheet of the parameter estimation of solar PV cell models

Characteristic Data	R.T.C France
I_{sc} (A)	0.7603
V_{oc} (V)	0.5728
V_{mp} (V)	0.4507
I_{mp} (A)	0.6894
R_{sh0} (Ω)	246.80
R_{s0}(Ω)	0.0907
T (K)	306.15
N	1

Table 4.5: Parameter estimation of PV cell for Four Diode Model at temperature 33 °C

Parameters/ Algorithm	Ipv	n1	n2	n3	n4	Rse	Rsh	Irsd1	Irsd2	Irsd3	Irsd4	RMSE	Comp Time (sec)
PSO	0.7034	1.0500	1.0214	1.0448	1.0309	2.0699E-03	15.8414	6.2463E-05	4.0913E-05	5.8214E-05	3.2217E-05	2.9927E-04	4.75
GWO	0.7432	1.5833	1.5020	1.4885	1.4964	2.3269E-03	55.8095	2.1551E-06	9.8510E-07	1.3932E-06	6.2792E-07	2.4560E-05	4.73
DOX	0.8032	1.3404	1.5675	1.5542	1.6725	4.3417E-04	32.0868	5.5017E-07	1.0924E-06	7.4561E-07	1.4973E-06	1.3884E-05	4.43
GWOCS	0.7627	1.8302	1.7602	1.8140	1.8036	1.0178E-02	33.3132	1.1698E-06	7.6594E-07	7.2318E-07	1.0665E-06	7.0323E-08	2.25
PSOGWO	0.7299	1.5692	1.5648	1.6828	1.6374	2.1158E-03	21.2850	5.7889E-04	1.2162E-05	2.0858E-06	1.3273E-03	2.6228E-08	2.23
HPSODOX	0.7990	1.5970	1.6517	1.5049	1.5018	1.2202E-03	31.4882	9.4830E-07	5.6654E-07	8.4271E-07	1.0911E-06	6.5656E-09	2.09

From Table 4.5, it is observed that HPSODOX has minimum value of RMSE as compared to other meta-heuristic algorithms i.e., 6.5656E-09. RMSE value of PSO is 2.9927E-04, GWO is 2.4560E-05, DOX is 1.3884E-05, GWOCS is 7.0323E-08 and PSOGWO is 2.6228E-08.

Table 4.6: Parameter estimation of PV cell for Four Diode Model at different temperatures

Celsius (°C)	Kelvin (K)	Parameters/ Algorithm	PSO	GWO	DOX	GWOCS	PSOGWO	HPSODOX
-5	268.15	I_{pv}	0.6620	0.7922	0.8031	0.6451	0.7160	0.7927
		n_1	1.0000	1.4416	1.4289	1.9238	1.5784	1.5133
		n_2	1.0000	1.4157	1.4367	1.9027	1.6260	1.5146
		n_3	1.0000	1.5858	1.5530	1.8996	1.7327	1.5997
		n_4	1.0000	1.4688	1.6924	1.8966	1.6154	1.5503
		R_{se}	2.7532E-04	2.5702E-03	6.6861E-04	1.5860E-02	3.4586E-04	1.4521E-03
		R_{sh}	20.7927	22.2305	18.8745	23.4423	11.8489	18.6122
		I_{rsd1}	1.6501E-05	1.5404E-07	3.0845E-07	7.9894E-07	1.2244E-03	1.5422E-07
		I_{rsd2}	2.9845E-05	1.7449E-07	3.1025E-07	9.5265E-07	3.8154E-03	4.4827E-07
		I_{rsd3}	3.8546E-04	4.3886E-07	1.9926E-07	7.6998E-07	4.9437E-04	2.3109E-07
		I_{rsd4}	3.6568E-04	1.5296E-07	4.5804E-07	7.4146E-07	3.9084E-03	3.2184E-07
		RMSE	6.4855E-05	4.4661E-05	1.0145E-06	2.4246E-07	3.6847E-08	2.2190E-08
		Comp Time (sec)	4.7188	4.5625	3.0938	2.2813	1.875	1.8594
0	273.15	I_{pv}	0.6627	0.7831	0.8071	0.6925	0.8287	0.7923
		n_1	1.0000	1.5383	1.4783	1.8403	1.4980	1.6617
		n_2	1.0000	1.5427	1.5426	1.8057	1.5318	1.5340
		n_3	1.0000	1.4033	1.4878	1.8610	1.5245	1.5312
		n_4	1.0316	1.5304	1.6158	1.9230	1.6347	1.5972
		R_{se}	4.6589E-05	5.3965E-03	4.7968E-04	1.1039E-02	3.2473E-04	3.8012E-03
		R_{sh}	20.7910	31.7278	20.3901	20.1786	10.3905	30.8791
		I_{rsd1}	7.6521E-05	8.2726E-07	1.9300E-07	4.2372E-07	6.1855E-04	1.9452E-07
		I_{rsd2}	5.3658E-05	2.2276E-	1.9177E-	4.5648E-	1.0813E-	3.8800E-07

				07	07	07	07	
		I_{rsd3}	3.5487E-05	3.8732E-07	1.9467E-07	4.5756E-07	7.3879E-04	8.2097E-07
		I_{rsd4}	2.7854E-05	7.4693E-07	5.8678E-07	3.8574E-07	7.2828E-04	1.9317E-07
		RMSE	5.3773E-05	2.6905E-05	1.0021E-05	9.9117E-08	6.8644E-08	2.4959E-08
		Comp Time (sec)	4.9688	4.7344	3.1719	2.2344	2.2031	1.9063
5	278.15	I_{pv}	0.6210	0.7935	0.7935	0.7471	0.7580	0.7996
		n_1	1.0365	1.4235	1.3031	1.8571	1.5169	1.3267
		n_2	1.0933	1.4968	1.3417	1.8738	1.4290	1.5420
		n_3	1.0364	1.5095	1.5051	1.8354	1.5860	1.5957
		n_4	1.0159	1.5032	1.5579	1.8360	1.4655	1.4236
		R_{se}	3.2584E-02	5.2594E-03	8.1937E-04	1.0842E-02	2.1886E-04	2.0960E-03
		R_{sh}	25.7426	20.6832	36.7589	27.9305	12.8709	21.5596
		I_{rsd1}	3.4210E-05	2.4132E-07	2.4108E-07	5.3416E-07	4.8109E-04	5.3595E-10
		I_{rsd2}	4.2651E-05	5.1011E-07	4.8586E-07	6.3545E-07	5.1070E-04	7.2369E-07
		I_{rsd3}	6.6587E-05	3.0000E-07	7.2625E-07	4.5394E-07	5.4446E-04	7.2475E-07
		I_{rsd4}	2.8263E-05	4.1047E-07	9.7763E-07	5.5280E-07	2.7925E-03	2.4111E-07
		RMSE	9.0488E-05	3.5856E-05	1.7609E-05	1.9686E-07	8.4815E-08	2.6624E-08
		Comp Time (sec)	4.7656	3.9063	3.1406	2.2031	2.0781	2.0313
10	283.15	I_{pv}	0.6209	0.7838	0.7992	0.7270	0.7541	0.7968
		n_1	1.0365	1.4486	1.5497	1.8752	1.5877	1.5691
		n_2	1.0989	1.4979	1.6474	1.8282	1.6070	1.6005
		n_3	1.0778	1.6395	1.4598	1.8844	1.5202	1.5015
		n_4	1.0731	1.5382	1.4151	1.8378	1.7048	1.4843
		R_{se}	2.276E-06	4.5025E-03	5.0527E-04	1.0579E-02	3.7515E-03	8.6246E-04
		R_{sh}	25.7425	32.2371	34.5275	29.4471	14.3167	32.7969
		I_{rsd1}	2.4861E-05	3.1730E-07	3.0070E-07	6.9009E-07	3.1119E-04	6.5513E-07

		I_{rsd2}	2.1404E-05	5.1121E-07	5.9842E-07	6.1122E-07	1.7851E-04	8.9611E-07
		I_{rsd3}	4.4938E-05	9.2499E-07	2.9686E-07	6.0136E-07	3.3997E-05	3.0053E-07
		I_{rsd4}	3.4399E-05	9.3434E-07	1.2004E-06	5.3568E-07	2.9286E-04	5.9323E-07
		RMSE	2.6537E-04	2.6461E-05	1.2369E-05	9.7283E-08	6.2059E-08	3.8490E-08
		Comp Time (sec)	4.9375	4.7031	3.0938	2.2969	2.2188	2.0625
15	288.15	I_{pv}	0.6208	0.7809	0.8081	0.7641	0.8157	0.7870
		n_1	1.0321	1.5388	1.4296	1.8465	1.5203	1.5787
		n_2	1.0000	1.4257	1.4445	1.7953	1.5157	1.5473
		n_3	1.0111	1.5740	1.4305	1.8291	1.6073	1.6502
		n_4	1.0000	1.5416	1.4326	1.8463	1.5156	1.5607
		R_{se}	3.1326E-04	4.0688E-03	9.7009E-04	1.1615E-02	2.0917E-03	2.3104E-03
		R_{sh}	25.7432	39.0494	21.9059	28.6977	8.7751	48.6937
		I_{rsd1}	2.3479E-05	1.0503E-06	3.6967E-07	8.2197E-07	1.1035E-04	1.5769E-06
		I_{rsd2}	4.8013E-05	7.5362E-13	7.1636E-07	6.5944E-07	1.9320E-03	6.5782E-07
		I_{rsd3}	5.3019E-05	2.1336E-06	3.6520E-07	6.8056E-07	7.9787E-03	1.3472E-06
		I_{rsd4}	4.6341E-05	3.7985E-07	3.6874E-07	6.6623E-07	3.1525E-03	8.3214E-07
		RMSE	6.7958E-05	5.2710E-05	1.1437E-05	1.3273E-06	3.4653E-08	1.8446E-08
		Comp Time (sec)	4.75	4.0938	3.1406	2.2188	2.125	1.6875
20	293.15	I_{pv}	0.7451	0.7843	0.7953	0.7646	0.7997	0.7958
		n_1	1.0093	1.4746	1.6527	1.8176	1.6145	1.7108
		n_2	1.0000	1.4289	1.4903	1.8344	1.6654	1.3861
		n_3	1.0000	1.4878	1.4725	1.8265	1.5726	1.5183
		n_4	1.0000	1.6832	1.6602	1.7984	1.5983	1.5701
		R_{se}	1.6934E-06	2.4113E-	8.5139E-	1.4525E-	1.2697E-	5.5638E-03

				03	04	02	03	
		R_{sh}	10.8913	43.7861	39.0619	31.2142	11.8398	38.3688
		I_{rsd1}	8.3879E-05	1.4570E-06	4.4629E-07	8.8405E-07	1.5901E-07	8.1615E-07
		I_{rsd2}	6.8621E-05	1.9808E-07	2.2461E-06	6.4411E-07	4.3511E-06	1.7576E-08
		I_{rsd3}	5.0148E-05	6.9811E-07	2.6183E-07	8.4944E-07	3.7336E-06	1.4330E-06
		I_{rsd4}	4.5544E-05	2.1984E-06	1.3369E-06	7.5697E-07	3.9419E-06	7.6578E-07
		RMSE	1.6969E-04	7.3448E-05	5.5440E-06	3.7711E-06	3.0402E-07	3.3515E-08
		Comp Time (sec)	4.5781	4.0625	3.0938	2.3594	1.9219	1.6094
25	298.15	I_{pv}	0.7452	0.7726	0.8090	0.7633	0.7399	0.8047
		n_1	1.0000	1.5569	1.5423	1.8191	1.6332	1.5363
		n_2	1.0000	1.4365	1.3543	1.7947	1.6785	1.3685
		n_3	1.0500	1.7184	1.4098	1.7875	1.5825	1.5690
		n_4	1.0000	1.5732	1.4782	1.7670	1.7313	1.5496
		R_{se}	3.1894E-04	2.3163E-03	2.3550E-04	9.8008E-03	4.1164E-04	2.3122E-03
		R_{sh}	10.8908	53.1209	21.9964	33.7751	12.7504	16.7599
		I_{rsd1}	5.2736E-05	2.0738E-06	6.4697E-07	1.2269E-06	7.4901E-03	1.2464E-06
		I_{rsd2}	4.8901E-05	7.5972E-07	6.5046E-07	8.2494E-07	2.5855E-03	5.5966E-08
		I_{rsd3}	5.0364E-05	2.3249E-06	1.9770E-06	1.1345E-06	5.0860E-03	2.6786E-07
		I_{rsd4}	3.5349E-05	1.8525E-06	6.5950E-07	7.6392E-07	3.8645E-03	6.0664E-07
		RMSE	1.3810E-04	3.4870E-05	9.8053E-06	7.2821E-08	5.0063E-08	3.1436E-09
		Comp Time (sec)	4.7969	4.0625	3.1094	2.3125	2.0781	1.6875

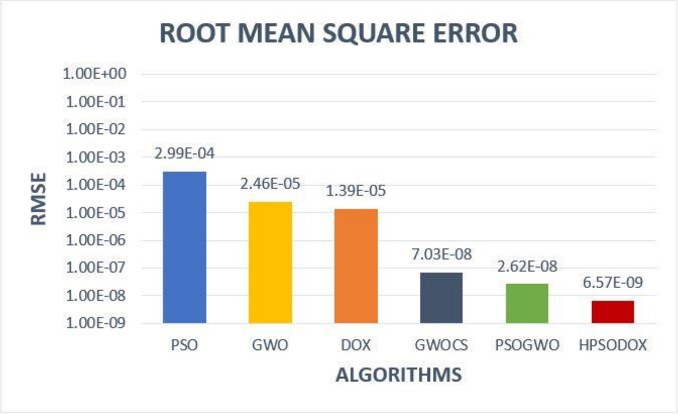


Figure 4.11: Bar Graph of RMSE at STC for Four Diode Model

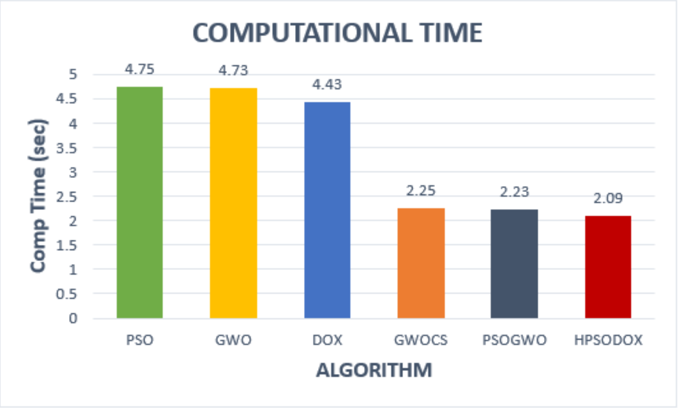


Figure 4.12: Bar Graph of Computational Time for Four Diode Model

4.2.3 Convergence Analysis

Figure 4.13 shows the convergence graph of four diode model of solar PV cell at 33 °C, and it clearly depicts that the HPSODOX algorithm has higher convergence pace as compared to other algorithms.

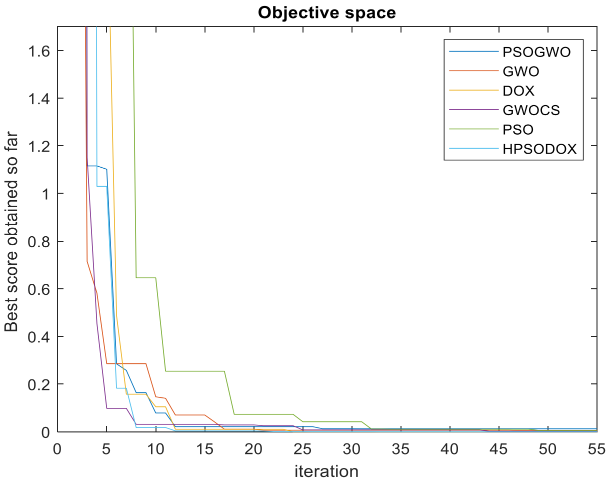


Figure 4.13: Convergence graph of Four Diode Model of solar PV cell at 33 °C

4.2.4 Non-Parametric Test

Table 4.7 represents the Friedman ranking test of the four diode model, this test clearly shows that the new developed (HPSODOX) algorithm outperforms existing algorithms in terms of accuracy, precision, and performance, with HPSODOX securing first rank, followed by PSOGWO, GWOCS, DOX, GWO, PSO. Figure 4.14 shows the Bar graph of Friedman Ranking Test for Four diode model.

Table 4.7: Friedman ranking test for Four diode model

Algorithms	Friedman ranking
DOX	4
GWO	5
GWOCS	3
PSOGWO	2
PSO	6
HPSODOX	1

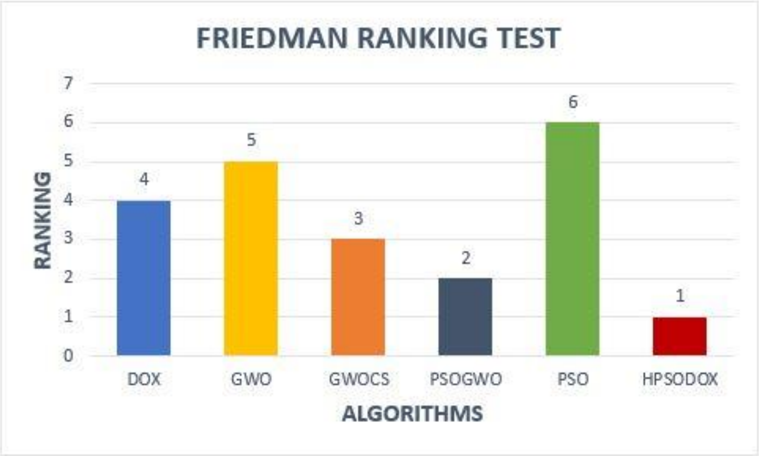


Figure 4.14: Bar graph of Friedman Ranking Test for Four Diode Model

Considering all the presented results, it is possible to conclude that HPSODOX is superior than other well-established algorithms for parameter estimation of solar PV cell models.

4.3 MODIFIED FOUR DIODE MODEL OF SOLAR PV CELL

4.3.1 Benchmark Test Functions

For modified four diode solar PV cell, developed hybrid (HPSODOX) algorithm is benchmarked on ten test functions as shown in Table 4.1. Table 4.8 represents the mean and the values of standard deviation (SD) evaluated by various algorithms on benchmark test functions. From the results, it is clear that hybrid (HPSODOX) algorithm performs better than other algorithms. Figures 4.15 to 4.24 show the bar graph of the value of the mean of 10 benchmark test functions using the proposed hybrid algorithm compared with PSO, GWO, DOX, GWOCS, and PSOGWO.

Table 4.8: Results of Benchmark Test Functions for Modified Four Diode Model

Algorithms		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
PSO	Mean	2.51E+03	1.59E+01	4.08E+04	8.73E+01	1.39E+07	4.84E+03	2.97E+00	-1.25E+03	3.60E+02	1.48E+01
	SD	1.62E+03	2.34E+01	6.52E+03	9.50E+00	2.58E+07	1.18E+04	1.14E+01	1.52E+02	1.81E+01	4.48E+00
GWO	Mean	3.83E+01	5.94E+00	1.32E+04	8.57E+00	5.29E+06	3.01E+03	1.88E+00	-4.05E+03	9.37E+01	5.19E+00
	SD	1.43E+02	1.57E+00	1.19E+04	2.18E+01	3.38E+06	1.88E+03	1.29E+00	2.94E+02	8.89E+01	5.64E+00
DOX	Mean	8.98E-15	7.41E-10	7.39E+01	2.32E-03	3.72E+01	1.94E+00	4.27E-03	-4.46E+03	2.36E+00	1.53E-08
	SD	1.19E-14	3.29E-10	1.27E+02	1.91E-03	8.02E-01	2.24E-01	2.86E-03	2.22E+02	3.21E+00	1.84E-08
GWOCS	Mean	5.28E-15	6.55E-20	5.02E-09	2.48E-08	3.61E+01	1.44E+00	2.03E-03	-7.10E+03	2.04E+00	4.87E-14
	SD	1.41E-14	4.20E-20	5.77E-09	2.62E-08	2.94E-01	2.24E-01	6.77E-04	4.93E+02	4.62E+00	2.57E-15
PSOGWO	Mean	7.66E-35	3.43E-20	2.36E-09	6.47E-09	2.76E+01	4.47E-01	7.82E-04	-7.28E+03	8.31E-14	4.25E-14
	SD	7.74E-35	2.25E-20	2.99E-09	5.76E-09	3.41E-01	3.89E-01	1.68E-04	7.85E+02	1.02E-13	4.09E-15
HPSODOX	Mean	1.15E-70	2.11E-43	8.20E-136	1.40E-19	0.00E+00	2.52E-01	1.59E-04	-2.20E+04	7.17E-16	5.74E-15
	SD	3.22E-70	3.76E-43	3.66E-135	3.28E-19	0.00E+00	2.33E-01	6.48E-05	2.26E+03	1.77E-15	3.35E-14

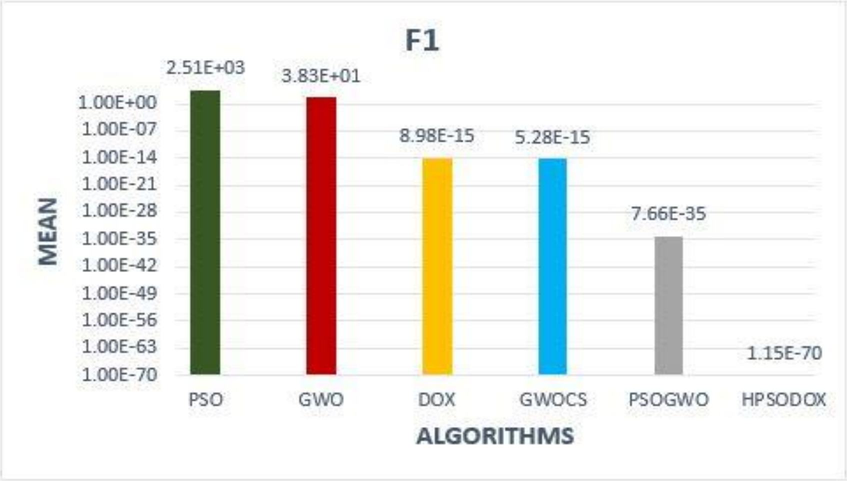


Figure 4.15: Bar graph of Benchmark Test Function, F1 for Modified Four Diode Model

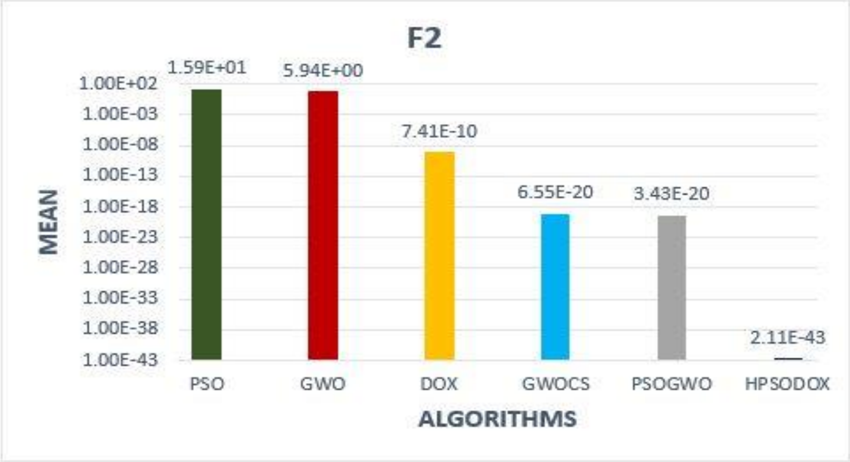


Figure 4.16: Bar graph of Benchmark Test Function, F2 for Modified Four Diode Model

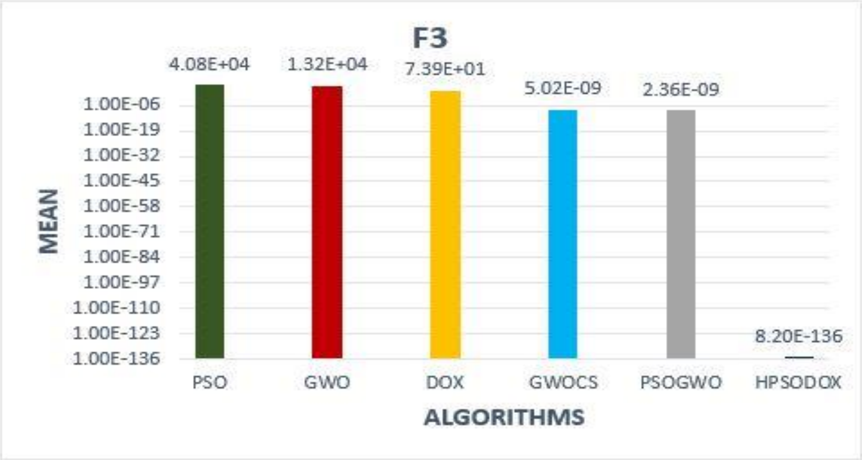


Figure 4.17: Bar graph of Benchmark Test Function, F3 for Modified Four Diode Model

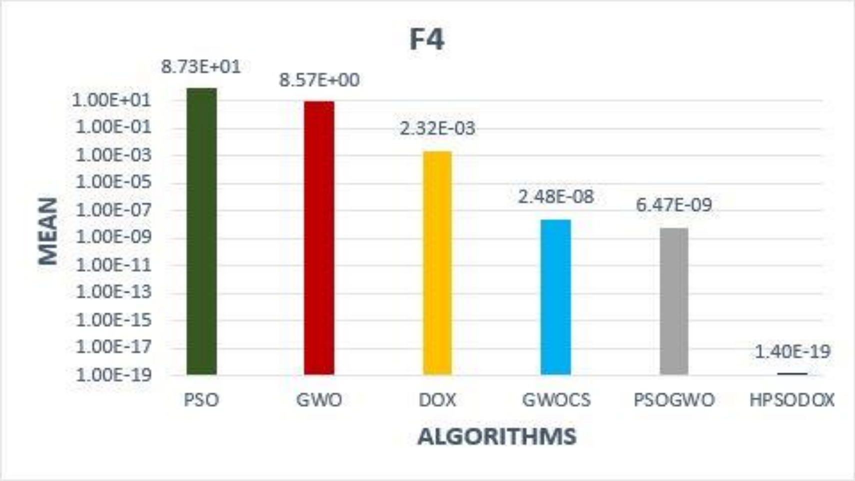


Figure 4.18: Bar graph of Benchmark Test Function, F4 for Modified Four Diode Model

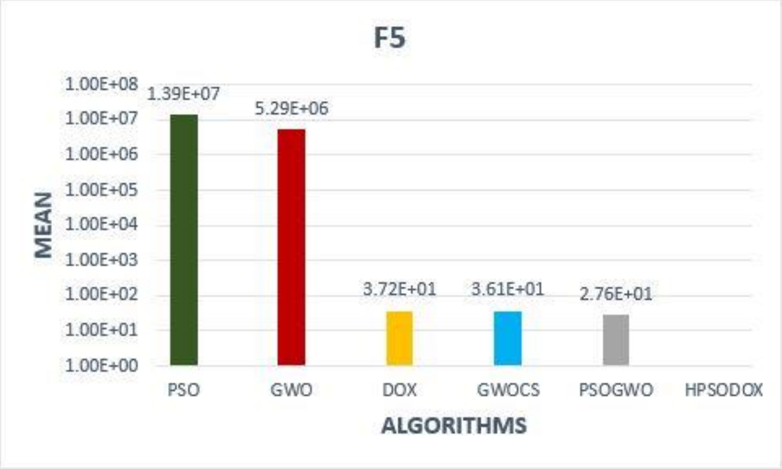


Figure 4.19: Bar graph of Benchmark Test Function, F5 for Modified Four Diode Model

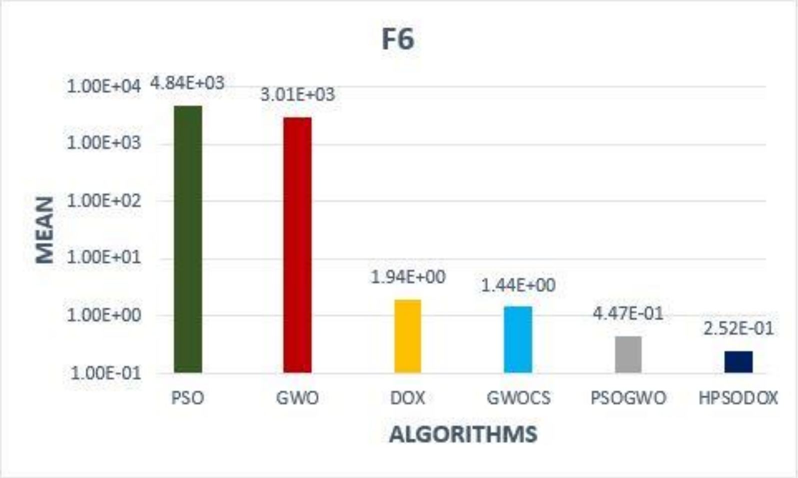


Figure 4.20: Bar graph of Benchmark Test Function, F6 for Modified Four Diode Model

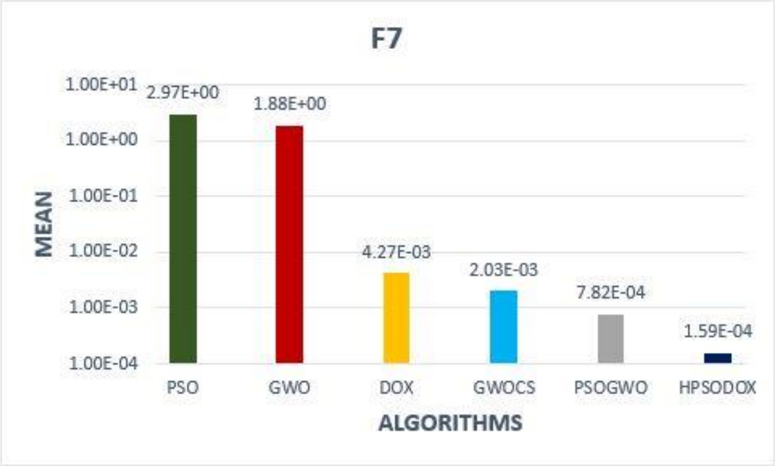


Figure 4.21: Bar graph of Benchmark Test Function, F7 for Modified Four Diode Model

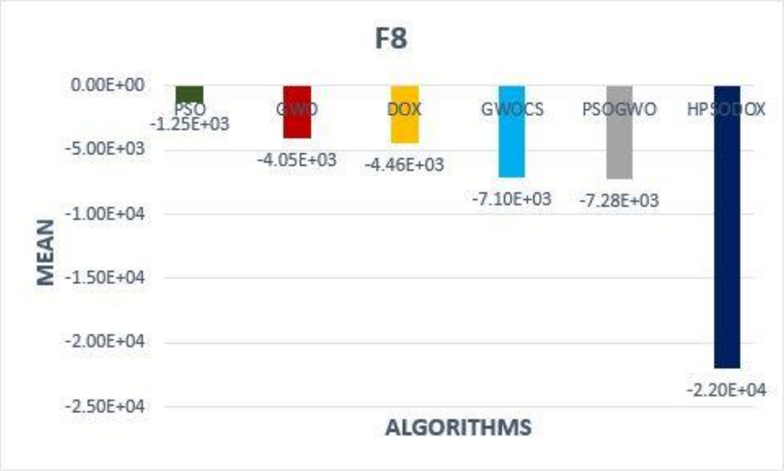


Figure 4.22: Bar graph of Benchmark Test Function, F8 for Modified Four Diode Model

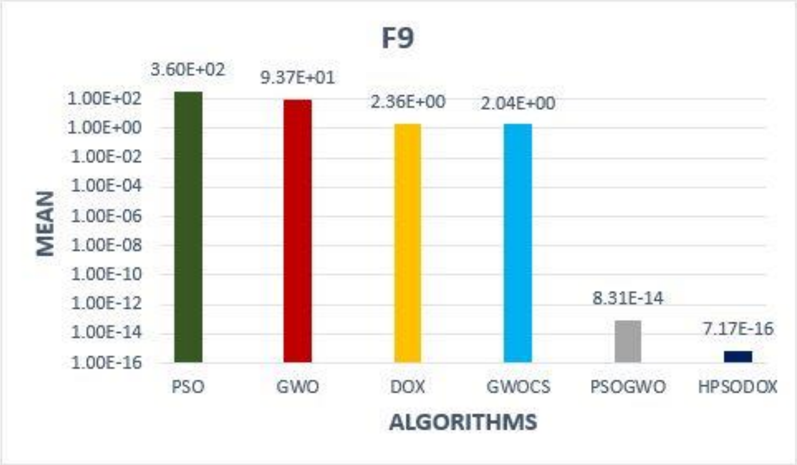


Figure 4.23: Bar graph of Benchmark Test Function, F9 for Modified Four Diode Model

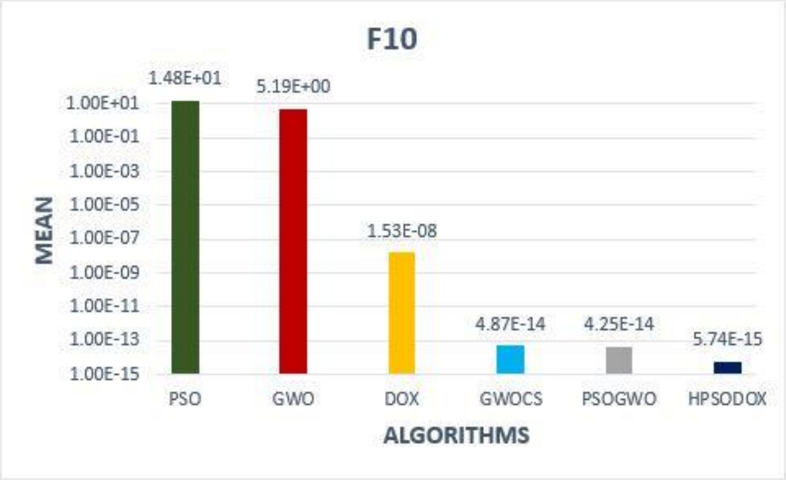


Figure 4.24: Bar graph of Benchmark Test Function, F10 for Modified Four Diode Model

4.3.2 Parameter Estimation

In case of parameter estimation of modified four diode solar PV cell, parameter search range and R.T.C. France data sheet is considered and shown in Table 4.9 and Table 4.4 respectively. New developed hybrid (HPSODOX) algorithm is used for parameter estimation of modified four diode solar PV cell. Further, the value of RMSE is calculated and compared with the other meta-heuristic algorithms i.e., PSO, GWO, DOX, GWOCS, PSOGWO which is shown in Table 4.10 and Table 4.11 at STC and different temperatures respectively. Figure 4.25 illustrates the Bar graph of RMSE values at STC. Figure 4.26 represents the bar graph of computational time for modified four diode model.

Table 4.9: Parameter Search Range for Modified Four Diode Model of solar PV cell

Parameters	Lower bound	Upper bound
I_{pv} (A)	0	1
I_{rsd1}, I_{rsd2}, I_{rsd3}, I_{rsd4} (μA)	0	1
R_{se} (Ω)	0	0.5
R_{sh} (Ω)	0	100
R_4(Ω)	0	2
n_1, n_2, n_3, n_4	1	2

Table 4.10: Parameter estimation of PV cell for Modified Four Diode Model at temperature 33 °C

Parameters/ Algorithm	Ipv	n1	n2	n3	n4	Rse	Rsh	Irsd1	Irsd2	Irsd3	Irsd4	R_4	RMSE	Comp Time (sec)
PSO	0.7143	1.9325	1.2046	1.4387	1.3116	2.6845E-03	19.3942	6.7813E-05	3.2158E-05	2.8430E-05	2.1025E-05	1.6221	3.1587E-05	4.827
GWO	0.7296	1.6371	1.4209	1.3658	1.5120	2.5275E-02	51.9415	3.6412E-06	7.8416E-07	3.8416E-05	5.1515E-07	1.3985	2.2058E-05	4.782
DOX	0.7431	1.5627	1.5934	1.5381	1.6025	4.7851E-04	35.4256	6.4515E-07	4.6105E-07	5.5416E-07	2.5125E-06	0.5165	3.5094E-07	4.518
GWOCS	0.7805	1.8722	1.5856	1.6938	1.5525	1.5841E-02	39.8125	2.5215E-06	2.5585E-07	1.6526E-07	3.5963E-06	0.4912	6.9415E-09	2.325
PSOGWO	0.7119	1.5871	1.6578	1.7826	1.7160	1.2210E-03	32.1251	4.0365E-04	4.5842E-05	2.6103E-06	1.4697E-03	0.4496	5.6352E-09	2.261
HPSODOX	0.7463	1.7945	1.7469	1.6254	1.5035	1.8457E-03	374.2622	8.5254E-07	7.4036E-07	6.9413E-07	1.6465E-06	0.1968	7.1037E-11	2.129

From Table 4.10, it is observed that HPSODOX has minimum value of RMSE as compared to other meta-heuristic algorithms i.e., 7.1037E-11. RMSE value of PSO is 3.1587E-05, GWO is 2.2058E-05, DOX is 3.5094E-07, GWOCS is 6.9415E-09 and PSOGWO is 5.6352E-09.

Table 4.11: Parameter estimation of PV cell for Modified Four Diode Model at different temperatures

Celsius(°C)	Kelvin (K)	Parameters / Algorithm	PSO	GWO	DOX	GWOCS	PSOGWO	HPSODOX
-5	268.15	I_{pv}	0.7125	0.7584	0.6504	0.6143	0.6941	0.7258
		n_1	1.0000	1.3232	1.3873	1.7511	1.6725	1.6524
		n_2	1.1126	1.5281	1.6312	1.8421	1.5467	1.6256
		n_3	1.0000	1.4525	1.6032	1.7298	1.5469	1.7208
		n_4	1.0000	1.5192	1.6349	1.7132	1.5066	1.7015
		R_{se}	3.1565E-04	3.9542E-03	4.5265E-04	2.4657E-02	2.8470E-04	2.9036E-03
		R_{sh}	32.4586	36.4699	33.4525	30.8051	12.6587	37.8417
		I_{rsd1}	1.7856E-05	2.8542E-07	4.3301E-07	8.1370E-07	1.8063E-04	5.6630E-07

		I_{rsd2}	1.6946E-04	2.5296E-07	2.0137E-07	6.9543E-07	2.9413E-03	3.0296E-07
		I_{rsd3}	2.4553E-04	3.5166E-07	2.8876E-07	7.1940E-07	3.5842E-03	2.0847E-07
		I_{rsd4}	2.4157E-05	4.7207E-07	3.5893E-07	6.0924E-07	4.7878E-03	3.5242E-07
		R_4	1.2366	1.5279	1.3629	1.4963	1.5247	0.8170
		RMSE	5.1090E-05	4.2877E-06	2.6493E-07	7.9153E-08	1.2846E-09	2.8194E-10
		Comp Time (sec)	4.742	4.628	3.131	2.348	1.937	1.874
0	273.15	I_{pv}	0.7116	0.7616	0.6501	0.6254	0.7021	0.7495
		n_1	1.1300	1.5001	1.4610	1.7036	1.5031	1.6113
		n_2	1.0000	1.5703	1.6388	1.7362	1.4655	1.6421
		n_3	1.0000	1.4303	1.4866	1.8036	1.5190	1.5445
		n_4	1.0000	1.4771	1.6760	1.7954	1.5421	1.7315
		R_{se}	5.1121E-05	5.2216E-03	3.9954E-04	1.1604E-02	2.0013E-04	3.1600E-03
		R_{sh}	32.5108	26.0079	32.8311	21.8069	15.9549	27.0896
		I_{rsd1}	6.3322E-05	7.0263E-07	1.8101E-07	3.2527E-07	5.1633E-04	3.5890E-07
		I_{rsd2}	6.0947E-05	8.7741E-07	1.5525E-07	3.4600E-07	2.1856E-07	3.4125E-07
		I_{rsd3}	5.4785E-05	2.8843E-07	1.9126E-07	2.6915E-07	6.5133E-04	4.0085E-07
		I_{rsd4}	4.8663E-05	6.2470E-07	2.6546E-07	3.1258E-07	8.3567E-04	4.6895E-07
		R_4	1.7474	1.2358	1.3548	1.3628	1.0585	1.4633
		RMSE	6.3215E-05	5.4210E-06	1.9125E-06	8.2879E-09	7.2255E-09	8.7037E-11
		Comp Time (sec)	4.991	4.763	3.237	2.276	2.243	1.939
5	278.15	I_{pv}	0.7293	0.7585	0.6535	0.6101	0.7015	0.7444
		n_1	1.1255	1.5040	1.6290	1.6625	1.5224	1.7407
		n_2	1.1959	1.4121	1.6249	1.8613	1.6278	1.7427
		n_3	1.1946	1.4460	1.5407	1.7551	1.5344	1.6509
		n_4	1.1288	1.4622	1.6497	1.7516	1.6372	1.6535
		R_{se}	4.3325E-02	3.1785E-03	5.1965E-04	2.4872E-02	2.2720E-04	4.4800E-03
		R_{sh}	21.8542	25.1425	35.4659	36.4586	19.4004	36.5529
		I_{rsd1}	3.4684E-	3.8003E-	2.7109E-	4.0028E-	3.2248E-	4.1448E-

			05	07	07	07	04	07
		I_{rsd2}	3.8036E-05	3.0365E-07	2.1695E-07	2.8422E-07	6.5485E-04	4.6410E-07
		I_{rsd3}	5.1126E-05	4.4010E-07	5.4414E-07	4.0985E-07	8.1581E-04	2.8746E-07
		I_{rsd4}	2.6652E-05	4.0094E-07	8.4721E-07	4.2222E-07	9.4889E-03	2.0846E-07
		R_4	1.8270	1.3624	1.3354	1.1370	1.1211	1.3854
		RMSE	6.5215E-05	2.1875E-06	4.6844E-07	7.5896E-09	7.4968E-09	5.4300E-11
		Comp Time (sec)	4.814	3.945	3.184	2.231	2.127	2.079
10	283.15	I_{pv}	0.7200	0.7545	0.6425	0.6211	0.7066	0.7455
		n_1	1.1375	1.5100	1.7094	1.7895	1.6875	1.5125
		n_2	1.1587	1.5698	1.6784	1.7984	1.5036	1.5852
		n_3	1.1746	1.4864	1.6442	1.6185	1.6200	1.6785
		n_4	1.1209	1.4216	1.5755	1.7525	1.7574	1.6582
		R_{se}	2.2945E-06	3.5487E-03	5.0200E-04	2.9111E-04	3.4470E-03	6.1889E-04
		R_{sh}	31.6985	38.0012	32.0112	35.9115	14.8770	35.2202
		I_{rsd1}	2.4130E-05	4.1036E-07	3.5036E-07	5.8472E-07	4.1186E-04	5.5215E-07
		I_{rsd2}	3.9815E-05	4.5040E-07	4.9215E-07	5.1255E-07	4.2037E-05	7.0726E-07
		I_{rsd3}	4.5845E-05	5.7842E-07	5.6946E-07	6.0785E-07	2.4858E-04	6.7857E-07
		I_{rsd4}	3.6609E-05	6.2216E-07	3.7459E-07	5.9149E-07	3.1179E-04	5.7827E-07
		R_4	1.5985	1.7137	1.1659	1.0211	1.3336	1.4124
		RMSE	4.8412E-05	2.5166E-06	7.7682E-07	5.7365E-09	4.5503E-09	5.8242E-11
		Comp Time (sec)	4.968	4.732	3.144	2.346	2.272	2.098
15	288.15	I_{pv}	0.7215	0.7511	0.6684	0.6412	0.7548	0.7219654
		n_1	1.0000	1.4412	1.5845	1.7524	1.5246	1.7037
		n_2	1.1458	1.5215	1.6585	1.7216	1.5485	1.6985
		n_3	1.1620	1.4625	1.6426	1.8699	1.5985	1.7895
		n_4	1.0885	1.5365	1.6694	1.7599	1.6325	1.7370
		R_{se}	3.1950E-04	4.5213E-03	8.1148E-04	1.8621E-02	1.5746E-03	2.4188E-03

		R_{sh}	34.2874	43.8037	34.3857	37.8449	11.8214	37.8137
		I_{rsd1}	3.0126E-05	8.5200E-06	3.8745E-07	8.1459E-07	2.7915E-04	2.7459E-06
		I_{rsd2}	4.1037E-05	6.8801E-13	4.9648E-07	7.0046E-07	2.3854E-03	2.2155E-07
		I_{rsd3}	2.8413E-05	6.9921E-06	5.2153E-09	6.8845E-07	2.6120E-03	2.9013E-07
		I_{rsd4}	3.8236E-05	7.0015E-06	5.1759E-07	6.9925E-08	4.6956E-03	3.8421E-07
		R_4	1.6355	0.8547	1.4985	1.3554	0.2985	0.7457
		RMSE	2.1782E-04	3.9926E-05	2.1586E-07	6.9459E-09	5.9875E-09	2.7621E-11
		Comp Time (sec)	4.812	4.155	3.17	2.249	2.285	1.728
20	293.15	I_{pv}	0.7388	0.7594	0.65214	0.6429	0.7519	0.723079
		n_1	1.1515	1.4855	1.5036	1.7128	1.6129	1.7255
		n_2	1.1954	1.5815	1.5266	1.8201	1.5897	1.7587
		n_3	1.1661	1.5642	1.6296	1.7469	1.6848	1.7022
		n_4	1.1283	1.5545	1.6849	1.7146	1.6258	1.6047
		R_{se}	2.6525E-06	3.4897E-03	7.0699E-04	2.8636E-02	2.5549E-03	1.9013E-03
		R_{sh}	40.5964	45.7459	35.9013	35.6780	11.4003	40.9515
		I_{rsd1}	6.2146E-05	2.7862E-06	7.5421E-07	7.1025E-07	1.4128E-06	6.8775E-07
		I_{rsd2}	5.0745E-05	1.5894E-07	6.1125E-06	7.1658E-07	2.4988E-06	3.0755E-07
		I_{rsd3}	5.4459E-05	2.4011E-07	5.5541E-06	6.8455E-07	4.0786E-06	3.8775E-08
		I_{rsd4}	6.3015E-05	3.1879E-06	4.9745E-07	5.1859E-07	2.7857E-06	2.4037E-07
		R_4	0.8127	1.2241	1.7825	0.5846	0.3337	0.4522
		RMSE	3.4475E-05	2.6431E-06	7.2549E-07	3.8459E-09	2.5126E-09	7.8546E-11
		Comp Time (sec)	4.548	4.101	3.114	2.463	1.968	1.627
25	298.15	I_{pv}	0.7321	0.7578	0.64158	0.63985	0.7291	0.756681
		n_1	1.1025	1.5126	1.7054	1.7018	1.6745	1.7814
		n_2	1.0000	1.5640	1.6825	1.7685	1.6022	1.6747
		n_3	1.0000	1.4789	1.6485	1.7426	1.6107	1.7214

		n_4	1.0000	1.4967	1.6725	1.7547	1.5876	1.7908
		R_{se}	2.8745E-04	3.7370E-03	3.9753E-04	3.7137E-03	4.2186E-04	4.0013E-03
		R_{sh}	45.4152	49.7125	35.8778	36.2213	10.5830	38.8874
		I_{rsd1}	4.4746E-05	7.2111E-06	2.2215E-07	4.4879E-06	6.3320E-03	5.5482E-06
		I_{rsd2}	4.3155E-05	7.3584E-06	2.7746E-07	4.5268E-06	5.2875E-03	4.0893E-07
		I_{rsd3}	3.6584E-05	6.2846E-06	3.8966E-07	5.1458E-07	3.5159E-03	4.1587E-08
		I_{rsd4}	5.6521E-05	5.6179E-06	3.9246E-07	4.7555E-06	3.5748E-03	3.0756E-07
		R_4	1.3785	1.2167	0.7455	0.6211	1.4897	0.9646
		RMSE	2.1699E-05	1.0785E-06	8.4775E-07	8.9221E-09	7.8892E-09	6.4684E-11
		Comp Time (sec)	4.952	4.172	3.132	2.356	2.128	1.623

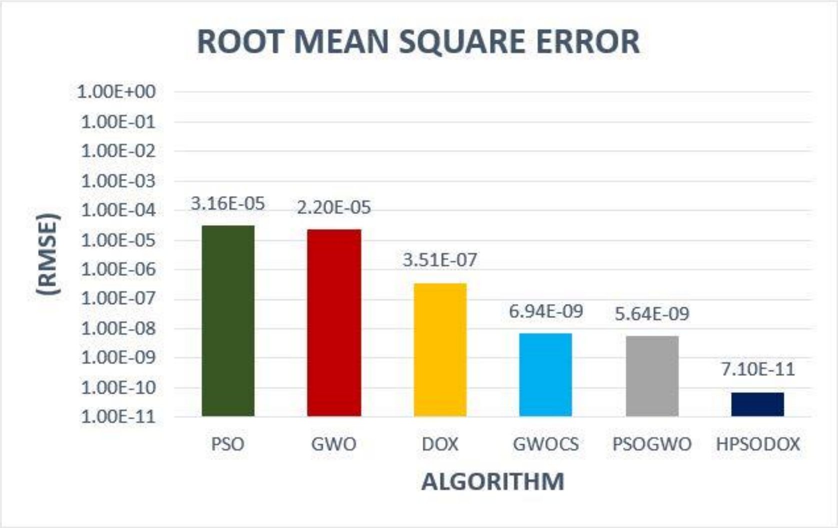


Figure 4.25: Bar Graph of RMSE at STC for Modified Four Diode Model

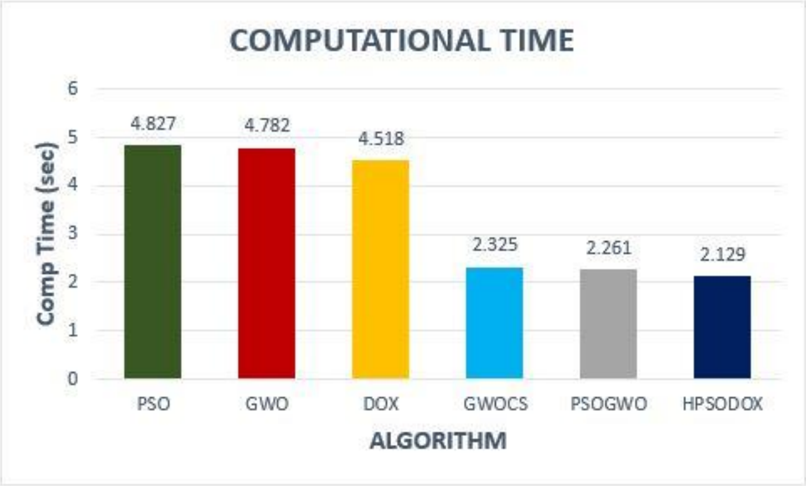


Figure 4.26: Bar Graph of Computational Time for Modified Four Diode Model

4.3.3 Convergence Analysis

The convergence graph of modified four diode model of solar PV cell at 33 °C is shown in Figure 4.27 which clearly illustrates that the HPSODOX algorithm has higher convergence pace in comparison to other algorithms.

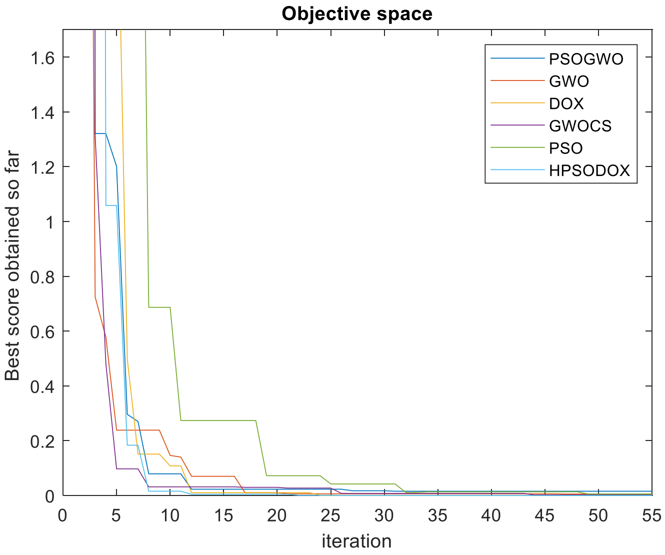


Figure 4.27: Convergence graph of Modified Four Diode Model of solar PV cell at 33 °C

4.3.4 Non-Parametric Test

Table 4.12 represents the Friedman ranking test of the modified four diode model of solar PV which clearly shows that the new developed (HPSODOX) algorithm is better than other algorithms with HPSODOX securing first rank, followed by PSOGWO, GWOCS, DOX, GWO, PSO. Figure 4.28 shows the bar graph of Friedman Ranking Test for four diode model.

Table 4.12: Friedman ranking test for Modified Four Diode Model

Algorithms	Friedman ranking
DOX	4
GWO	5
GWOCS	3
PSOGWO	2
PSO	6
HPSODOX	1

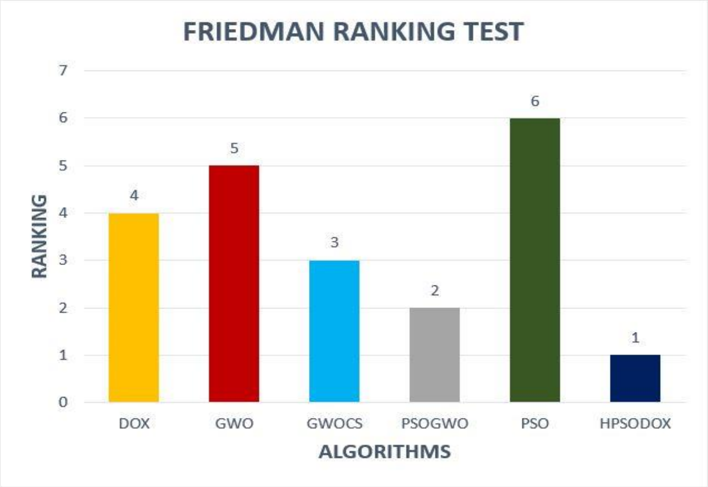


Figure 4.28: Bar graph of Friedman Ranking Test for Modified Four Diode Model

All the above presented results illustrate that HPSODOX algorithm outperforms other well-known meta-heuristic algorithms to estimate the parameters of modified four diode model of solar PV cell.

4.4 PROTON EXCHANGE MEMBRANE FUEL CELL (PEMFC)

4.4.1 Benchmark Test Functions

For evaluation of the proposed hybrid algorithm i.e., HPSODOX for parameter estimation of PEMFC, 10 benchmark test functions are selected as shown in Table 4.1. Each function’s dimension is set to 40. The values of mean and Standard Deviation (SD) of the benchmark test functions are shown in Table 4.13. The results clearly show that the proposed hybrid algorithm that is, HPSODOX has significantly better performance than other meta-heuristic algorithms. Figures 4.29 to 4.38 illustrate the bar graph of the value of the mean of 10 benchmark test functions using the proposed hybrid algorithm compared with PSO, GWO, DOX, PSOGWO, and GWOCS.

Table 4.13: Benchmark test functions results for PEMFC

Algorithms		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
PSO	mean	1.54E+04	6.52E+07	8.70E+04	87.70	6.12E+07	1.84E+04	22.80	-4.58E+03	4.23E+02	17.80
	SD	5.26E+03	2.01E+08	1.24E+04	4.9	3.42E+07	4.66E+03	6.95	3.72E+02	21.10	2.35
GWO	mean	3.99E+03	37.30	1.33E+04	7.6	9.33E+04	6.86E+03	1.45E-01	-5.02E+03	1.70E+02	7.5
	SD	1.11E+04	8.28	2.88E+04	15.50	2.76E+05	1.65E+04	1.69E-01	2.93E+02	1.84E+02	8.28
DOX	mean	4.81E-09	9.35E-07	7.34E+03	2.31E-01	37.20	3.56	9.40E-03	-7.80E+03	8.7	1.17E-05
	SD	6.91E-09	5.96E-07	7.01E+03	2.14E-01	8.53E-01	2.78E-01	3.70E-03	9.17E+02	13.90	8.08E-06
GWOCS	mean	1.03E-27	8.33E-17	5.89E-05	1.62E-06	36.50	2.64	2.16E-03	-8.35E+03	1.99	1.17E-13
	SD	1.11E-27	3.61E-17	1.54E-04	1.49E-06	5.64E-01	6.04E-01	1.03E-03	2.27E+03	4.86	1.85E-14
PSOGWO	mean	1.37E-28	4.05E-17	1.20E-05	6.42E-07	26.90	9.49E-01	1.58E-03	-1.34E+04	9.98E-01	8.22E-14
	SD	1.18E-28	2.43E-17	2.49E-05	6.81E-07	4.16E-01	4.05E-01	5.92E-04	1.57E+03	2.14	1.07E-14
HPSODOX	mean	4.01E-72	7.83E-38	1.25E-131	1.94E-16	0	8.59E-01	8.05E-05	-1.64E+04	8.12E-08	4.77E-15
	SD	9.88E-72	2.48E-37	3.97E-131	4.72E-16	0	4.61E-01	4.01E-05	3.14E+02	2.83E-15	4.72E-14

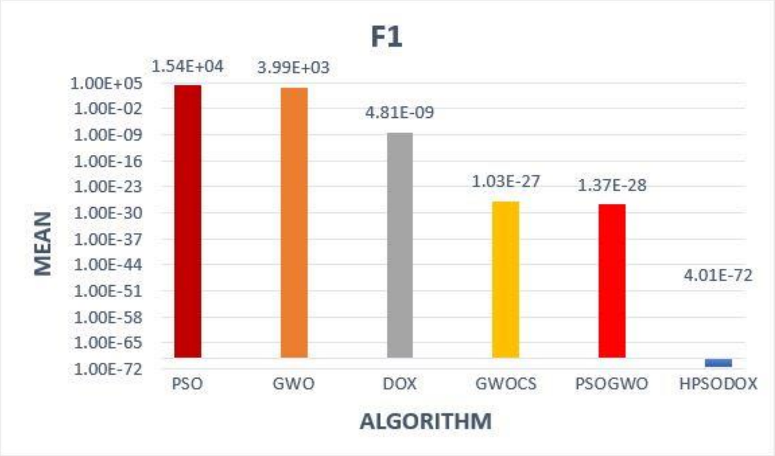


Figure 4.29: Bar graph of Benchmark Test Function, F1 for PEMFC

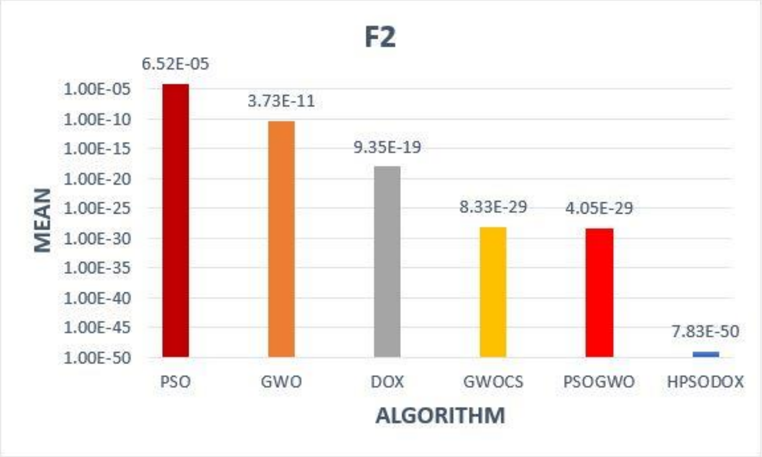


Figure 4.30: Bar graph of Benchmark Test Function, F2 for PEMFC

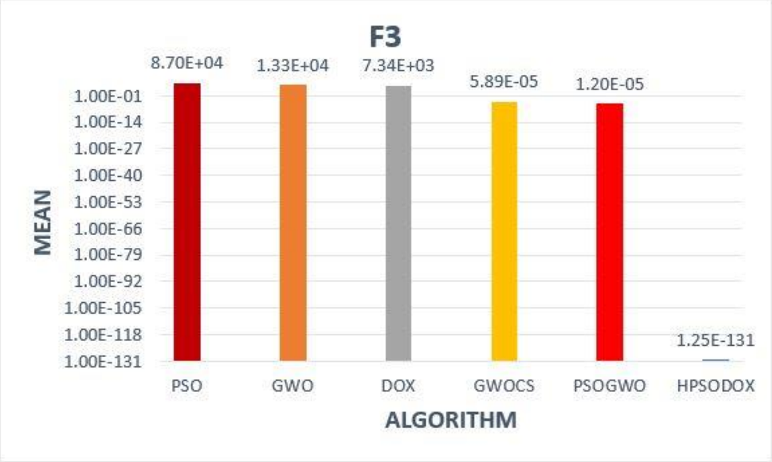


Figure 4.31: Bar graph of Benchmark Test Function, F3 for PEMFC

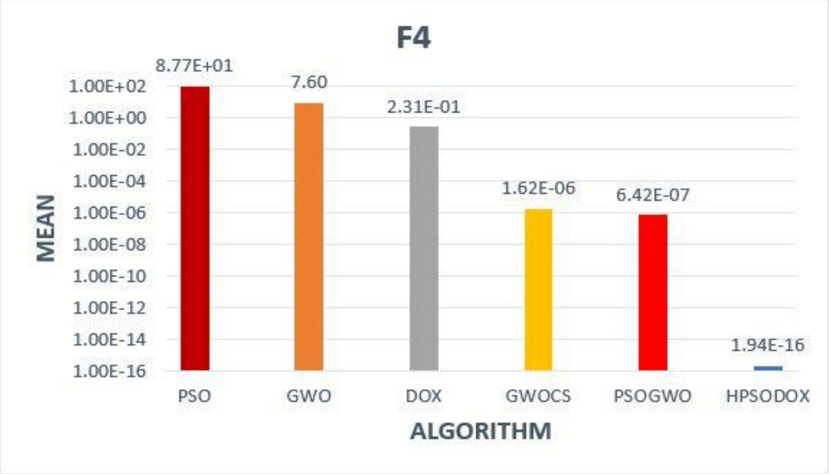


Figure 4.32: Bar graph of Benchmark Test Function, F4 for PEMFC

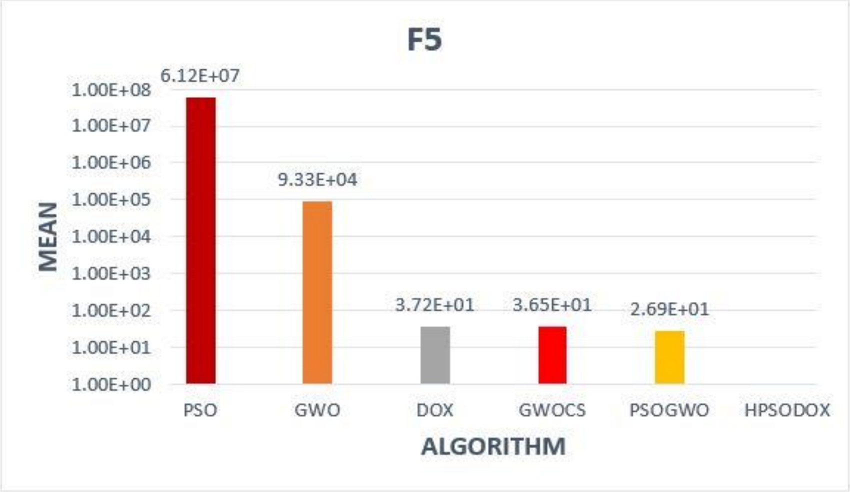


Figure 4.33: Bar graph of Benchmark Test Function, F5 for PEMFC

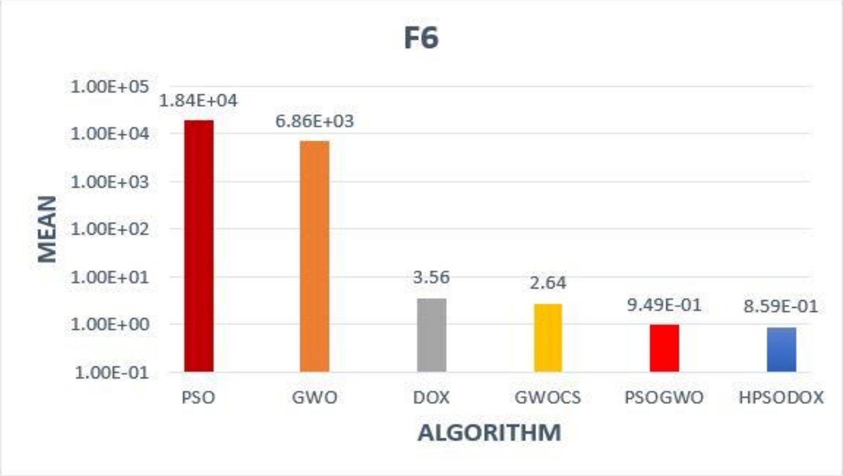


Figure 4.34: Bar graph of Benchmark Test Function, F6 for PEMFC

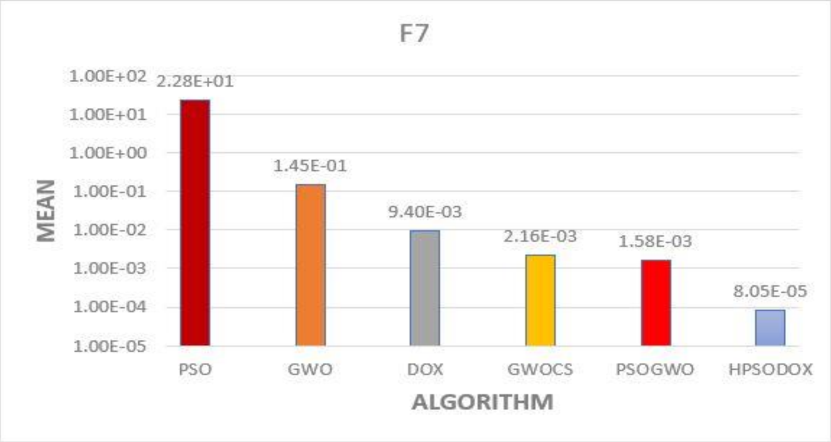


Figure 4.35: Bar graph of Benchmark Test Function, F7 for PEMFC

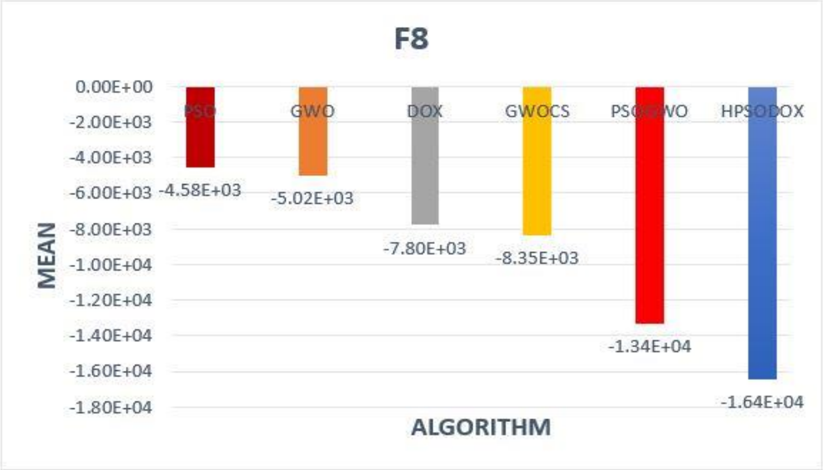


Figure 4.36: Bar graph of Benchmark Test Function, F8 for PEMFC

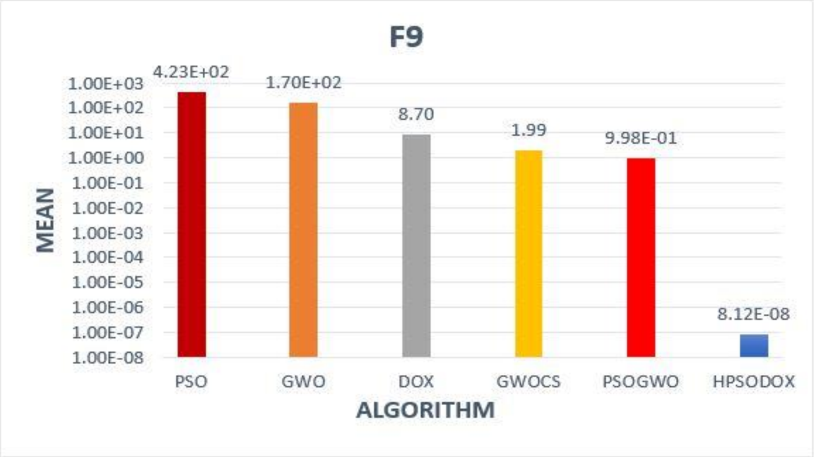


Figure 4.37: Bar graph of Benchmark Test Function, F9 for PEMFC

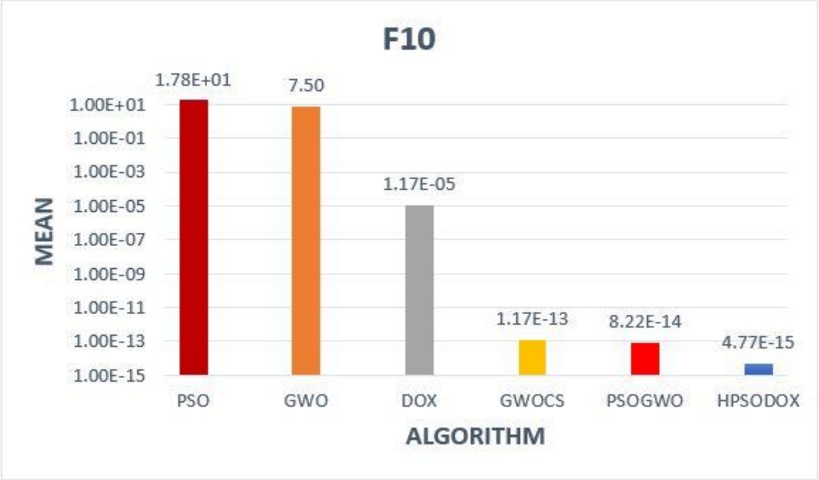


Figure 4.38: Bar graph of Benchmark Test Function, F10 for PEMFC

4.4.2 Parameter Estimation

The parameter search range taken for estimating the parameters of PEMFC is shown in Table 4.14. Table 4.15 represents the datasheet of Ballard Mark V for the same. For parameter estimation of PEMFC, population size is set to 50 and the feature evaluation limit is kept as 1000 for an effective assessment. After parameter estimation of PEMFC, the performance and efficiency of a new proposed hybrid algorithm, that is, HPSODOX is compared with other algorithms i.e., PSO, DOX, GWO, PSOGWO, and GWOCS. Parameter estimation of PEMFC at standard temperature condition (STC) i.e., 70 ℃ (343.15 K) is represented in Table 4.16.

Table 4.14: Upper and lower bound range

Parameters	Upper bound	Lower bound
ε_1	-0.08532	-1.1997
$\varepsilon_2 \times 10^{-3}$	6.00	0.8
$\varepsilon_3 \times 10^{-5}$	9080	3.60
$\varepsilon_4 \times 10^{-4}$	-0.954	-2.60
λ	24.00	10.00
$R_c \times 10^{-4}$	8.00	1.00
b	0.5	0.0136

Table 4.15: Datasheet of Ballard Mark V

Model	Ballard Mark V
n	35
$A\ [cm^2]$	50.6
$l\ [\mu m]$	178
$J_{max}\ [A/cm^2]$	1.5
P_{H_2}[bar]	1
P_{O_2}[bar]	1
Power [W]	1000
T [K]	343.15

Table 4.16: Parameter estimation of PEMFC

Parameter/Algorithms	ε_1	ε_2	ε_3	ε_4	λ	R_{CR}	b	SSE	Comp Time (sec)
PSO	-0.9844	0.0023	6.8365E-05	-1.7813E-04	15.7602	0.00046	0.2147	2.2486E-04	4.90
GWO	-1.0649	0.0025	6.3497E-05	-1.5295E-04	18.0219	0.00036	0.1842	3.0519E-05	4.70
DOX	-1.0342	0.0028	5.1895E-05	-1.0642E-04	12	0.00042	0.2562	2.6155E-05	2.98

GWOCS	-1.0089	0.0025	6.7893E-05	-1.8846E-04	17.9012	0.00038	0.2369	6.0440E-08	2.52
PSOGWO	-1.0568	0.0025	5.8458E-05	-2.6801E-04	17.2647	0.00048	0.2559	3.5465E-08	2.37
HPSODOX	-1.1754	0.0012	4.5421E-05	-1.3716E-04	12.3347	0.00035	0.2459	7.8451E-09	2

After estimating the parameters of PEMFC, the value of Sum of Square Error (SSE) and computational time (in sec) is calculated as shown in Table 4.16, and bar graph of SSE for all algorithms is shown in Figure 4.39. From this, it is clear that the value of SSE is minimum for the proposed hybrid algorithm, HPSODOX i.e., 7.8451E-09 when compared to other algorithms. The value of SSE for PSO is 2.2486E-04, DOX is 2.6155E-05, GWO is 3.0519E-05, GWOCS is 6.0440E-08, and PSOGWO is 3.5465E-08, thus proving it to be a better and efficient algorithm in order to estimate the parameters of PEMFC. Further, the value of computational time is minimum for the proposed algorithm. Bar graph of computational time is shown in Figure 4.40.

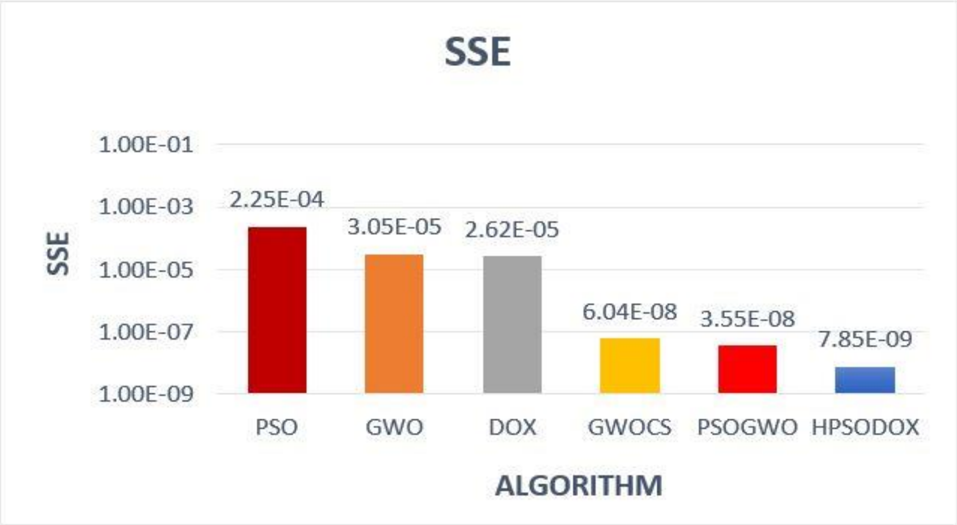


Figure 4.39: Bar Graph of Sum of Square Error (SSE) for PEMFC

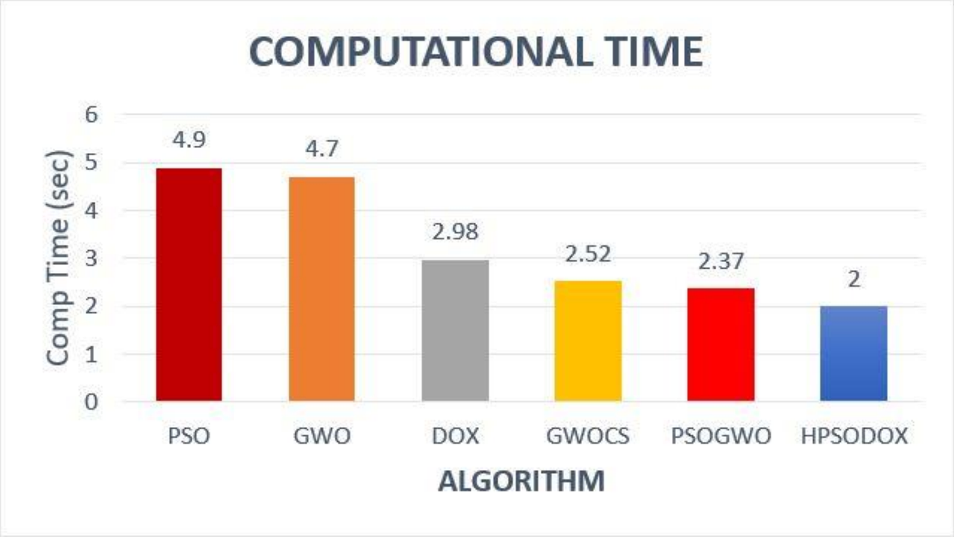


Figure 4.40: Bar Graph of Computational Time for PEMFC

4.4.3 Convergence Analysis

Figure 4.41 represents the convergence graph of HPSODOX and its comparison with other algorithms that is, PSO, DOX, GWO, GWOCS, and PSOGWO. From the graph, it is clear that there is a higher pace of convergence in case of the proposed hybrid algorithm as compared to other algorithms. Therefore, HPSODOX is more accurate and precise than other algorithms.

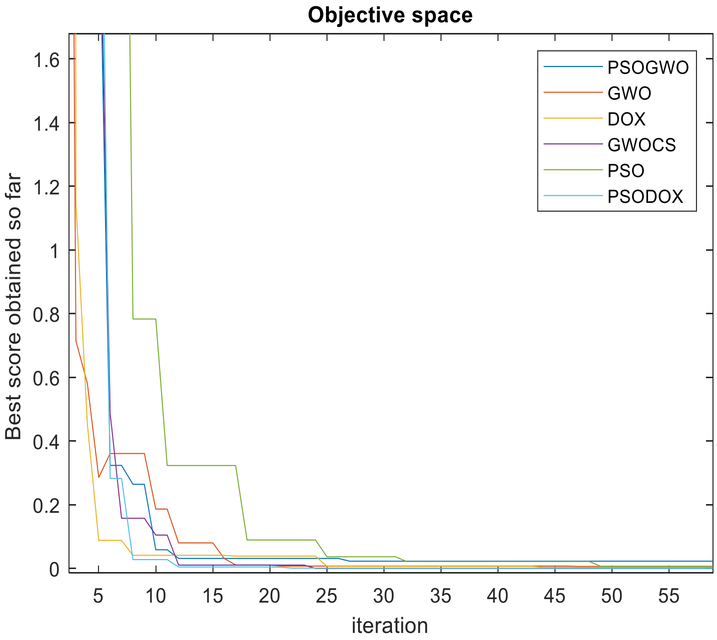


Figure 4.41: Convergence Graph for PEMFC

4.4.4 Non-Parametric Test

The non-parametric test of parameter estimation of PEMFC is carried out with Friedman ranking test results as represented in Table 4.17 and Figure 4.42 shows the Bar Graph of Friedman Ranking Test where HPSODOX has secured the first rank, followed by PSOGWO, GWOCS, DOX, GWO, and PSO, respectively. The non-parametric test results depict that the proposed hybrid algorithm, HPSODOX, has better performance than other meta-heuristic algorithms in measure of efficiency, accuracy, precision, and robustness.

Table 4.17: Friedman ranking test for PEMFC

Algorithms	Friedman ranking
DOX	4
GWO	5
GWOCS	3
PSOGWO	2
PSO	6
HPSODOX	1

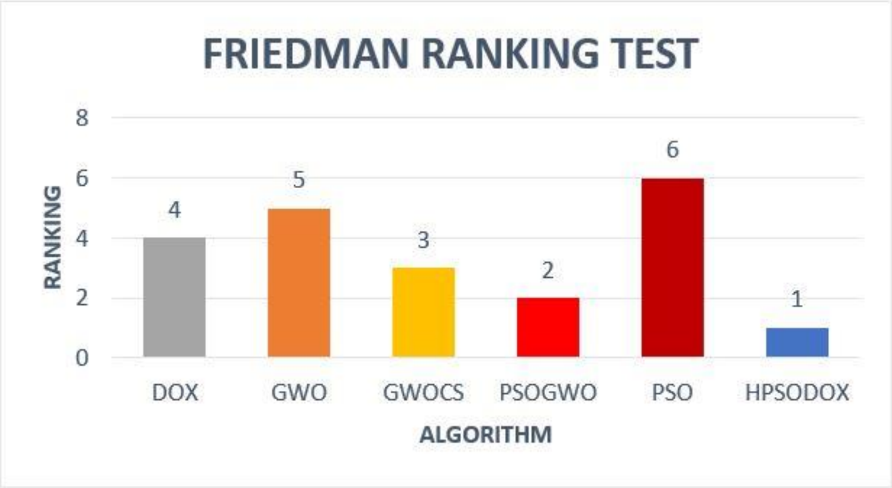


Figure 4.42: Bar Graph of Friedman Ranking Test for PEMFC

CHAPTER 5

CONCLUSIONS AND FUTURE SCOPE OF WORK

5.1 CONCLUSION

This work presents a new hybrid algorithm i.e., HPSODOX for parameter estimation of Solar Cell and PEMFC based on Particle Swarm Optimization (PSO) and Dingo Optimizer (DOX) meta-heuristic algorithms for obtaining the optimal set of solution for optimization problems. In this work, the datasheet of RTC France and Ballard Mark V is considered for parameter estimation of Solar Cell and PEMFC respectively.

On the basis of results obtained so far, the findings are outlined as following.

1. For parameter estimation of Solar Cell and PEMFC model, a new hybrid algorithm (HPSODOX) based on Particle Swarm Optimization (PSO) and Dingo Optimizer (DOX) was proposed.
2. For justification of the proposed algorithm, 10 benchmark functions were performed and the values of mean and Standard Deviation (SD) were calculated which shows that HPSODOX performs better than other meta-heuristic algorithms.
3. Parameter estimation of Solar Cell and PEMFC was done at STC using the proposed algorithm. The respective values of RMSE and SSE along with computational time were compared with other algorithms. It is clearly depicted from the minimum value of RMSE, SSE and computational time for the proposed algorithm that accuracy and efficiency of HPSODOX is better than other meta-heuristic algorithms.
4. Convergence graphs of HPSODOX and other algorithms show the higher pace of convergence of the proposed hybrid algorithm, thus proving it to be better than other meta-heuristic algorithms in order to find an optimal set of solutions.
5. Further, statistical analysis using Friedman Ranking test results also illustrated the better performance and robustness of the new proposed algorithm as HPSODOX secured first rank in Friedman Ranking Test results.

5.2 FUTURE SCOPE OF WORK

In this work, various meta-heuristic algorithms were explored in order to estimate the parameters of Solar PV Cell and PEMFC. Further, meta-heuristic algorithms can be applied to more variants of Solar PV Cell and parameter estimation of Solar PV Cell and PEMFC can be done using datasheets of other manufacturers. Proposed algorithm can further be explored in various other areas of renewable energy such as wind energy, biomass etc. as well as hybrid renewable energy system.

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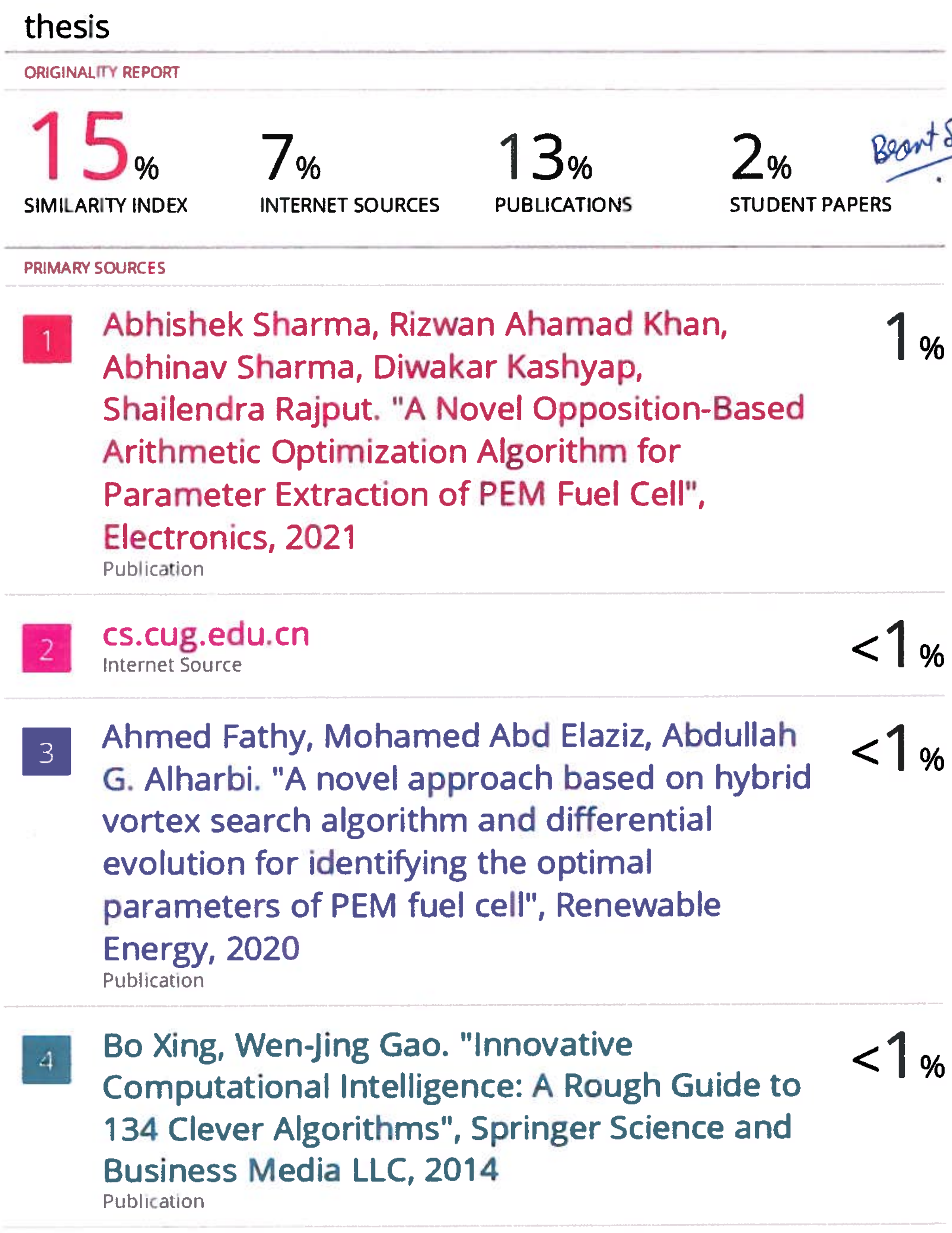

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