REPUBLIC OF TURKIYE
ISTANBUL GELISIM UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

Department of Electrical and Electronics Engineering

DETERMINATION OF OPTIMAL SOLAR CELL PARAMETERS USING IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

Master Thesis

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Supervisor

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THESIS INTRODUCTION FORM

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Turkish Abstract	**:** Kaynaklar, enerji de dahil olmak üzere hızlı küresel gelişme nedeniyle sürekli artan bir talebe sahiptir. Enerji ihtiyaçlarını karşılamak için petrol ve kömürün yakılması, fosil yakıt rezervlerinin tükenmesine, çevresel kirlenmeye, iklim değişikliğine ve diğer ilişkili sorunlara neden olabilir. Bu nedenle, fosil yakıtlardan yenilenebilir enerjiye geçiş, bu sorunların önerilen çözümü olarak kabul edilmektedir. Yenilenebilir enerji rüzgar, jeotermal, biyokütle ve güneş enerjisini içermektedir. Güneş enerjisi, saflığı, kirlilikten yoksun olması, yeterli rezervlere sahip olması ve uzun vadeli kullanım

potansiyeli nedeniyle umut verici bir alternatif enerji kaynağıdır. Bu sistemler güneş radyasyonunu doğrudan elektriğe dönüştürerek güneş pillerini en uygun yenilenebilir enerji kaynaklarından biri haline getirir. Bu tezde güneş pillerinin doğru modellemesi önemli bir konudur. Parametreler, modelin sonuçlarının gerçek sistem ölçümlü verileriyle eşleşmesi şeklinde belirlenmelidir. Güneş pili karakteristikleri (gerilime göre akım eğrisi) son derece doğrusal olmadığından, geleneksel klasik yöntemlerle sistemin belirlenemeyen parametrelerini tanımak imkansızdır. Bu nedenle, akıllı algoritmalar kullanılmalıdır. Fotovoltaik piller için optimal ayarları bulmak için birçok algoritma geliştirilmiştir, ancak bunların birçoğu aynı temel hatalı noktalarda takılı kalma sorununu paylaşır. Ayrıca, güneş hücresi parametrelerinin belirlenmesi sorununu çözmek için kullanılan bazı algoritmalar yavaş yakınsama hızına sahip olup zaman zaman dağılabilir. Yerel optimumlara takılmaktan kaçınmak için yakınsama ile yüksek doğruluk dengesine sahip bir algoritma gerekmektedir. Bu tezde güneş hücresi parametreleri belirlenmiş ve ortalama hata gücü, geliştirilmiş bir PSO algoritması kullanılarak en aza indirilmiştir. Bu araştırma için tek diyotlu, çift diyotlu ve üç diyotlu güneş hücresi modelleri dikkate alınmıştır. Amaç fonksiyonunun sonuçları, üç diyotlu modelin üstün performansa sahip olduğunu, bunu çift diyotlu ve tek diyotlu modellerin takip ettiğini göstermiştir ve bunların kök ortalama kare hata değerleri sırasıyla 6.966263e-04, 7.28000e-04 ve 7.7299e-04 olarak bulunmuştur. En uygun güneş hücresi modelinin noktalarını belirleyerek çeşitli algoritmaların simülasyon sonuçlarını karşılaştırdık. Bulgularımız, bazı algoritmalara kıyasla algoritmamızın daha doğru sonuçlar ürettiğini. Bu bulgular, güneş hücrelerinin performansını artırmak için tekniklerimizin verimli olduğunu desteklemektedir. Ayrıca, optimizasyon prosedüründen elde edilen tahmini parametrelerin gerçek sonuçlarla yüksek bir tutarlılık derecesine sahip olduğu gözlemlenmiştir.

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

Hamsa Abdulkareem NASHOOR

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The thesis study of Hamsa Abdulkareem NASHOOR titled as DETERMINATION OF OPTIMAL SOLAR CELL PARAMETERS USING IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM has been accepted as MASTER THESIS in the department of Electrical and Electronics Engineering by our jury.

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SUMMARY

The escalating pace of global development has resulted in a persistent rise in the demand for resources, particularly energy. The combustion of petroleum and coal to satisfy energy requirements can result in the exhaustion of fossil fuel reserves, environmental contamination, climate alteration, and other associated issues. As a result, switching from fossil fuels towards renewable energy has been recognized as the recommended remedy for these issues. Renewable energy comprises wind, geothermal, biomass, and solar. Solar energy is a promising alternative energy source due to its purity, absence of pollution, sufficient reserves, and potential for long-term usage. These systems directly convert solar radiation into electricity, making solar cells one of the most appropriate renewable energy sources. The matter of accurate modeling of these cells is the major topic in this thesis. The parameters should be determined in such a manner that the outcomes of the model match the actual system's measured data. Since the characteristics of a solar cell (current curve regarding voltage) are extremely non-linear, it is impossible to recognize the undetermined parameters of the system using traditional classical methods. Therefore, intelligent algorithms need to be employed. Although many algorithms have been developed to find the optimal settings for photovoltaic cells, many of them share the same major flaw: they get stuck in local optimal points. Furthermore, some algorithms used to resolve the issue of identifying solar cell parameters have a sluggish rate of convergence and intermittent divergence. In order to prevent becoming stuck in the local optima, an algorithm that balances convergence with high accuracy must be given.

The solar cell parameters were identified, and the average error power was minimized in this thesis using an improved PSO algorithm. For this investigation, we have taken into account solar cell models with 1- diode, 2- diodes, and 3- diodes. The outcomes of the objective function revealed that the three-diode model had the superior performance, followed by the two-diode and single-diode models with root mean square error values of 6.966263e-04, 7.28000e-04, and 7.7299e-04 respectively. We compared the simulation outcomes of various algorithms to the ones we got by identifying the points of the optimal solar cell model. Our findings indicate that compared to some algorithms, our algorithm produced more accurate results. These findings provide support that our technique for improving the performance of models of solar cells is productive. Furthermore, it has been observed that the estimated parameters obtained from the optimization procedure exhibit a high degree of consistency with actual results.

Key Words: Solar cell, Optimization methods, PSO, Parameter estimation

ÖZET

Kaynaklar, enerji de dahil olmak üzere hızlı küresel gelişme nedeniyle sürekli artan bir talebe sahiptir. Enerji ihtiyaçlarını karşılamak için petrol ve kömürün yakılması, fosil yakıt rezervlerinin tükenmesine, çevresel kirlenmeye, iklim değişikliğine ve diğer ilişkili sorunlara neden olabilir. Bu nedenle, fosil yakıtlardan yenilenebilir enerjiye geçiş, bu sorunların önerilen çözümü olarak kabul edilmektedir. Yenilenebilir enerji rüzgar, jeotermal, biyokütle ve güneş enerjisini içermektedir. Güneş enerjisi, saflığı, kirlilikten yoksun olması, yeterli rezervlere sahip olması ve uzun vadeli kullanım potansiyeli nedeniyle umut verici bir alternatif enerji kaynağıdır. Bu sistemler güneş radyasyonunu doğrudan elektriğe dönüştürerek güneş pillerini en uygun yenilenebilir enerji kaynaklarından biri haline getirir. Bu tezde güneş pillerinin doğru modellemesi önemli bir konudur. Parametreler, modelin sonuçlarının gerçek sistem ölçümlü verileriyle eşleşmesi şeklinde belirlenmelidir. Güneş pili karakteristikleri (gerilime göre akım eğrisi) son derece doğrusal olmadığından, geleneksel klasik yöntemlerle sistemin belirlenemeyen parametrelerini tanımak imkansızdır. Bu nedenle, akıllı algoritmalar kullanılmalıdır. Fotovoltaik piller için optimal ayarları bulmak için birçok algoritma geliştirilmiştir, ancak bunların birçoğu aynı temel hatalı noktalarda takılı kalma sorununu paylaşır. Ayrıca, güneş hücresi parametrelerinin belirlenmesi sorununu çözmek için kullanılan bazı algoritmalar yavaş yakınsama hızına sahip olup zaman zaman dağılabilir. Yerel optimumlara takılmaktan kaçınmak için yakınsama ile yüksek doğruluk dengesine sahip bir algoritma gerekmektedir. Bu tezde güneş hücresi parametreleri belirlenmiş ve ortalama hata gücü, geliştirilmiş bir PSO algoritması kullanılarak en aza indirilmiştir. Bu araştırma için tek diyotlu, çift diyotlu ve üç diyotlu güneş hücresi modelleri dikkate alınmıştır. Amaç fonksiyonunun sonuçları, üç diyotlu modelin üstün performansa sahip olduğunu, bunu çift diyotlu ve tek diyotlu modellerin takip ettiğini göstermiştir ve bunların kök ortalama kare hata değerleri sırasıyla 6.966263e-04, 7.28000e-04 ve 7.7299e-04 olarak bulunmuştur. En uygun güneş hücresi modelinin noktalarını belirleyerek çeşitli algoritmaların simülasyon sonuçlarını karşılaştırdık. Bulgularımız, bazı algoritmalara kıyasla algoritmamızın daha doğru sonuçlar ürettiğini. Bu bulgular, güneş hücrelerinin performansını artırmak için tekniklerimizin verimli olduğunu desteklemektedir. Ayrıca, optimizasyon prosedüründen elde edilen tahmini parametrelerin gerçek sonuçlarla yüksek bir tutarlılık derecesine sahip olduğu gözlemlenmiştir.

Anahtar kelimeler: Güneş pili, Optimizasyon yöntemleri, PSO, Parametre tahmini

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ABBREDIVATIONS

PV	:	Photovoltaic Energy
TDM	:	Three-Diode Model
DDM	:	Double Diode Model
SDM	:	Single Diode Model
PSO	:	Particle Swarm Optimization
IJAYA	:	Improved JAYA Algorithm
PGJAYA	:	Performance-guided JAYA algorithm
GOTLBO	:	Generalized Oppositional teaching-learning based optimization
WHHO	:	Whippy Harris Hawks Optimization algorithm
EHHO	:	Enhanced Harris Hawk Optimization
CS	:	Cuckoo search
GA	:	Genetic algorithm
SC	:	Solar cell
DE	:	Defferential Evaluation

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INTRODUCTION

The widespread consumption of fossil fuels like oil, coal, and gas leads to environmental damage and climate change. There is a conflict between the readily available fossil fuels and the worldwide need for energy (Humada et al., 2020). Damage to our natural environment and energy concerns are currently among the most significant challenges to human progress. Solar energy is one of several renewable energy sources that humans have been making use of due to its negligible environmental impact and inexpensive nature. Although the costs of solar energy systems are considerable, the positive aspects of using solar energy, such as minimised environmental impact, are considered in current policies.

Photovoltaic (PV) energy has recently been increasingly employed because of its reliability, cleanliness, and scalability. A photovoltaic system is any device which employs a natural phenomenon referred to as photovoltaics and generates electricity from light radiation without the aid of any driving mechanisms. Unlike petroleum and coal, which are non-renewable and will, at some point, run out, solar energy is a renewable source. Therefore using photovoltaic systems allows us to maintain our planet clean while still providing us with power (Long et al.., 2020).

Solar energy, one of the major contributors to the energy investment portfolio, accounts for the greatest share of electrical energy generation among all renewable energy remedies. Due to it being one of the most secure, trustworthy, and naturally replenishing forms of power available. The PV grid-connected source system is one of the most popular residential markets in many regions, including Europe, Japan, and the United States.

Solar photovoltaic (PV) systems are generally reliable and can generate power on most days of the year, though their output may vary from day to day and season to season due to seasonal and diurnal changes in the sun's intensity. Snow, clouds, rain, and the quantity of vegetation cover are some of the elements that might reduce the amount of energy produced. Additionally, solar cells may be location-dependent. If there is a significant amount of shade, solar panels may not be able to generate enough power.

A single, tiny PV cell could generate between 1 and 2 volts of energy. To increase their energy production, PV cells must be combined to form a module, a large unit. However, the output voltage of PV modules is a bit low. When multiple modules are joined together, the resulting panel is a larger unit that is capable of producing more energy. Modules are typically connected in series to provide higher voltage, and a solar array is the collection of solar panels strung together to gather sunlight and generate power. For a home grid system, the PV arrays which generate the necessary electricity are often installed on the roof.

Consequently, the amount of electricity produced by PV arrays with series structures becomes less when subjected to partial shading conditions caused by obstructions such as clouds, trees, or nearby buildings. Compared to a series configuration, the efficiency of the parallel configuration of these PV arrays is significantly higher. The output current could be increased thanks to the parallel arrangement of PV arrays, while the voltage stays unchanged. Combining parallel and series connections between solar cells can produce the required electrical current and voltage.

Solar power has probably the greatest potential of any alternative energy source. However, it has its shortcomings too. The operational point of a standard photovoltaic (PV) cell or module is subject to fluctuations in output power, which are attributed to environmental circumstances, specifically temperature T and irradiance G. Significant challenges, including low photoelectric conversion efficiency and uncertain modelling of PV cells, still beset the practical deployment of photovoltaic (PV) cells. Additionally, partial shading scenarios, which involve only a portion of the PV system being shaded, present further obstacles to their effective implementation (Ahmed and Miyatake, 2008)(Ma et al.., 2013)(Seyedmahmoudian et al.., 2013)(Chen et al.., 2010).

The precise determination of model parameters is a crucial prerequisite for a simulation model to demonstrate features that closely mirror the actual system's features (Vimalarani and Kamaraj, 2015).

In light of the nonlinear characteristics of photovoltaics and their extreme sensitivity to radiation level and operating temperature, the development of PV panel models remains a subject of active research.

The comprehension of the solar cell's nature, acquisition of its efficiency equations, and attainment of the highest efficiency possible necessitate a suitable mathematical model of the solar cell. In recent years, many models have been presented, ranging from simple to complicated, to account for solar cells' non-linear characteristics (I-V and P-V curves).

Several models have been developed and published in this context, such as the single diode model (SDM) (Humada et al., 2016), the double diode model (DDM) (R. Abbassi et al., 2018), the triple diode model (TDM) (Khanna et al., 2015), the improved single diode model (ISDM) (A. Abbassi et al., 2017), the SDM with a parasitic capacitor (Suskis and Galkin, 2013), the IDDM (Kurobe and Matsunami, 2005), the MDDM, the diffusion-based model (Lumb et al., 2013), and the multi-diode model (Soon et al., 2014). However, in actual use, researchers and professionals have focused mostly on single-diode and two-diode models. The analysis and performance of solar cells rely heavily on the parameters determined by these two models.(Bonanno et al., 2012)(Shaik et al., 2023).

Meanwhile, the correctness of the model changes with the values of the anticipated parameters. Unfortunately, it can be difficult to set constant values for these characteristics based on manufacturer datasheets due to their fluctuation over time. Therefore, valid and trustworthy PV modelling depends on a set of carefully chosen parameters. Consequently, as a result of this. To achieve a close tracking of experimentally measured I-V characteristics, it is recommended to adopt an optimised parameter estimation strategy for the PV model.

In this thesis, we employed an improved version of the particle swarm optimization method to determine the unknown variables of solar cells and modules. An improved PSO algorithm variant was created by (Li and Coster, 2022) . The proposed approach utilized the core ideology of genetic algorithm and dynamic parameters.

CHAPTER ONE

PURPOSE OF THE THESIS

1.1. Literature survey

It has always been essential, but in recent years there has been a lot of focus placed on the pursuit of high precision and dependability in the process of obtaining the key model parameters. (Nunes et al., 2018). Estimating the characteristics of solar cells and modules has been the focus of multiple research projects.

Electrical models of photovoltaic (PV) systems consist of several parameters. Due to the absence of appropriate model parameters that characterise PV cells, it is not possible to apply these models directly. The field of study referred to as parameter estimation offers methods and tools for determining values of variables that are found in the models (Beck and Arnold, 1977). The disparity between the simulated data and the experimental data can be reduced to a minimum by using the parameters that are derived in such a way.

In literature, Parameters of PV models have been estimated from measured I-V data using Analytical, Numerical, Meta-Heuristic algorithm approaches. At first, efforts were made to develop analytical methods, such as the use of simple and fast solutions based on mathematical equations. The accuracy of the model was, however, adversely impacted by the initial state assumptions. (Ortiz-Conde et al.., 2006; Saleem and Karmalkar., 2009).

Researchers have spent a lot of time trying to find analytical expressions that can be used to estimate physical parameters like the value of the coefficient of diffusion of electrons in semiconductors, the duration of the existence of minority carriers,and the intrinsic carrier density, etc. (Nishioka et al., 2007). However, manufacturers rarely disclose these values, compelling researchers to seek an alternate method of formulating the parameters from the datasheet.

Analytical techniques establish approximate relationships between experimental data and results. Despite their simplicity, they typically depend on the critical points of the I-V curve. Incorrectly specifying these central points can lead to serious errors that cannot be fixed in any other way.

Numerical extraction techniques, aided by a statistical method, effectively fit multiple operational points on the I-V curves to get an accurate answer (Gottschalg et al., 1999)(Appelbaum et al., 1993)(Gottschalg et al., 1997). These curve-fitting techniques minimise the root mean square error (RMS). Since all the collected data can be incorporated into the calculation, numeric extraction methods are typically seen as accurate approaches to parameter estimation. Nonetheless, their performance also depends on the fitting algorithm type, expense function, and initial parameter values (Gottschalg et al., 1999). Mathematically and programmatically, non-linear curve-fitting procedures are quite complicated. Moreover, the computational cost of the algorithms may be high owing to the magnitude of the necessary data (Easwarakhanthan et al.., 1986).

The limitations of these techniques declare them inappropriate for determining photovoltaic cell parameters (Lu et al., 2023). Meta-heuristic methods are employed to address optimization problems as a means of compensating for the limitations of deterministic approaches.

Meta-heuristic algorithms have a number of benefits over deterministic methods due to the fact that they are inspired by natural phenomena like swarm behaviour, evolutionary stages, and natural events, proved to be an adequate solution for a wide variety of multimodal, multidimensional, constrained, linear, and optimisation problems. Recent years have seen the application of meta-heuristic techniques for parameter extraction in PV models to minimise the shortcomings described earlier. (Lu et al.., 2023).

Jiang et al.., (2013) utilised the classical method of least squares to fit functions to a given dataset. They compared the effectiveness of the Gauss-Newton and Lunberg-Marquard methods in the parameter identification of a real solar cell sample. The results indicate that the least squares method is appropriate for the parameter identification of solar cells. This study is limited by its susceptibility to outliers and the potential for least square methods to become trapped in local rather than global minima (Jiang et al., 2013).

Intelligent methods, which are typically modelled after the way nature behaves, seek to come as close as possible to finding the best possible answer. For example, the bee optimization technique was used to determine the photovoltaic cell's parameters in (Ye et al., 2009). This algorithm, despite how easy it is to use, moves slowly through sequential processing, which means that it cannot be quickly converted to produce the best result.

The maximum power point of the solar cell is also estimated by (Patel et al., 2013) , who used the birds mating method to identify the solar cell's unknown parameters. The BMO method performs admirably in a variety of optimisation evaluations. Unfortunately, it is not a useful method for pinpointing the optimal solution spaces. In several cases, BMO demonstrates inefficient or early convergence.

The differential evolution approach was utilised by (Ishaque et al., 2011), to obtain the parameters for the single-diode model. The single-diode model and the two-diode module were employed in their approach; however, the algorithm they used was neither tested nor implemented.

Rao and Patel (Rao and Patel, 2012). proposed a parameter identification method based on the PSO search to determine the solar signal cell parameters of the single-diode and two-diode models.PSO's common use in resolving complex optimisation problems originates from its low complexity and high efficiency. However, only a single diode and double diode module have been presented in their approach.

(Easwarakhanthan et al.., 1986) employed the partial differential equation (P-DE) technique to determine the photovoltaic modules' various parameters, including photocurrent, diode saturation currents, diode ideal coefficients, series resistance, and parallel resistance. The findings demonstrate that the proposed method requires fewer control parameters and has higher accuracy and convergence speed when compared to similar methods.

Besides the aforementioned algorithms, the genetic algorithm (Sandrolini et al., 2010), the particle assembly algorithm (Orioli and Di Gangi., 2013), and other algorithms (Bonanno et al., 2012) (Amrouche et al., 2012) were also used to determine the variables of the single and double-diode photovoltaic cell models, each of which has weaknesses and strengths. In all the mentioned methods, the main criterion of optimization has been to minimize the difference between the laboratory results and the results obtained from the circuit model.

Using advanced data-processing technologies like neural networks, (Wang et al.., 2021) enriched datasets of solar cells using measured current-voltage data. Therefore, in, a different enhanced equilibrium optimizer is suggested to address parameter identification issues for the 1-diode model, 2-diode model, and 3-diode model. The Improved equilibrium optimiser uses a back propagation neural network to forecast extra yield data of photovoltaic cells, enabling it to implement a more efficient optimisation with a more plausible fitness function than the original equilibrium optimizer. The disadvantage of this investigation is the time required to process the data.

In (Garip et al., 2023), a novel algorithm approach based on fractal maps is proposed to enhance the search efficacy of the Harris Hawks optimisation (HHO) algorithm. Using the fractal Henson chaotic map, the random parameter that is effective in besieging the prey during the exploration and exploitation phases of the HHO algorithm is modified. The suggested Fractional Henon Chaotic Harris Hawks Optimisation (FCHHHO) algorithms and variants were tested on a variety of unimodal, multimodal, and fixed-dimension benchmark functions to ensure they provided the best possible outcomes. Their research has the potential drawback of becoming stuck in a local optimum.

A PV cell model was used to conduct an uncertainty analysis based on functional failure in (Zhang et al., 2023). Functional failure occurs as output power fluctuations that exceed the specified range, whereas the functional safety region is defined as the acceptable range of output power fluctuations during operation.

Using a global sensitivity analysis technique based on the Monte Carlo method, the effect of parameter variation on the functional failure probability of a PV cell was investigated. The investigation's shortcoming relies on the variable number. The Monte Carlo method has produced satisfactory results in terms of error when the variable number is set to five (in a single diode module). It takes a long time and a lot of computations to estimate a solution using this method when a lot of variables are restricted by different constraints.

Parameter estimation of the 3- diode model is presented as an application of a freshly developed optimisation technique, Northern Goshawk Optimisation (NGO), by Mahmoud A. El-Dabah et al. In this research, three commercial PV modules are used for the job. These types include mono-crystalline Canadian Solar CS6K-280 M, multi-crystalline Photowatt-PWP201, and Kyocera KC200GT (El-Dabah et al., 2023).

To figure out these parameters rapidly and more precisely than many meta-heuristic algorithms, the musical chairs algorithm (MCA) is introduced in (Eltamaly et al., 2022). The concept of using MCA is to start with many search agents to improve exploration and then gradually decrease the number of search agents to improve exploitation at the end of optimisation and speed up convergence. Ten different optimisation techniques were used, and the findings showed that the error associated with MCA was 20% of the average error of the other optimization algorithms.

Tummala.S. L. V. Ayyarao et al. Inspired by traditional military tactics, introduced a new metaheuristic optimisation algorithm (Ayyarao and Kumar, 2022). The proposed algorithm for optimising military strategy in war is called war strategy optimisation (WSO). Each soldier's actions are modelled as an optimisation process to reach an optimum global value. Each one of the soldiers is given a different weight; their location is constantly adjusted according to the previous round's success percentage.

Analytical and meta-heuristic approaches have been used thus far to derive the model parameters that are currently unknown.

Using various operating conditions and the values provided in the manufacturer datasheets, a nonlinear solar PV characteristic can be created using an analytical approach. Although these techniques are easy in concept, their level of accuracy greatly relies on the selection of a limited number of specific data points. In some instances, if these particular factors are incorrect, the accuracy of the results will be compromised. Consequently, their dependability is a significant concern.

The meta-heuristic approach, on the other hand, predicts the IV curve using a curve-fitting technique, where all of the projected data points on the IV curve are identical to the actual values. (Lim et al., 2015) (Ocaya and Yakuphanoglu, 2021) (Macabebe et al., 2011) (Tay et al., 2017) (Gu et al., 2023). Furthermore, it has been observed that the outcomes align with the actual characteristic curve of PV solar, with a low error. It is also possible to recreate any temporal variation in insolation or temperature. In general, these techniques are classified as (a) evolution-based, (b) nature-based, (c) human-based, and (d) bio-inspired.

In this thesis, we used the modified version of the particle swarm optimisation algorithm. The proposed method has been explained in chapter three. Our work indicates that the proposed algorithm has more accuracy than other algorithms such as multiple learning backtracking search algorithm (MLBSA), improved JAYA algorithm (IJAYA), generalised oppositional teaching-learning based optimisation (GOTLBO), Genetic algorithm (GA) and cuckoo search (CS) algorithm. The improved version of the PSO that we used in this thesis has accurate results. To maximise accuracy and diversify the population, the suggested algorithm utilized the core ideology of genetic algorithm and dynamic parameters.

1.2. Problem Statement

Determining an accurate solar cell model is crucial because doing so is the initial step in simulating, regulating, analysing, creating, and optimising the solar cell. The level of precision in calculations is positively correlated with the degree of accuracy in the model. As a result, the alignment between the simulation outputs and real-world outcomes will be improved.

In recent years, a significant amount of research has been conducted in solar cell modelling. The determination of the exact position of the maximum power point is of great significance, as it represents the optimal operating point of the solar cell, where the combined effect of the voltage and current maximises the output power to the load. The attainment of the maximum power point across diverse operational conditions is of paramount importance, given that the precise location of this point is contingent upon the prevailing environmental factors. The direct approach for determining the maximum power point is deemed to be a more appropriate and precise technique compared to alternative methods that are presently accessible. The voltage-current relationship of the solar cell is obtained, and the maximum power point is determined by evaluating the power output corresponding to the terminal voltage. The accuracy of the direct method is conditioned upon the accuracy of parameter determination for the given system. The inadequacy of conventional classical techniques in determining the unknown parameters of a solar cell system can be attributed to the non-linear nature of the relationship between voltage and current. The implementation of intelligent algorithms is deemed necessary in such a scenario.

The identification of solar cell parameters has been accomplished through diverse methodologies, albeit with a primary limitation of susceptibility to entrapment within local optima. Furthermore, specific algorithms employed for identifying optimal values about solar cell characteristics exhibit a sluggish convergence rate or may even diverge completely. In order to avoid the issue of becoming trapped in local optima, it is imperative to propose an algorithm that possesses the dual characteristics of convergence and exceptional precision.

To determine the parameters, it is necessary to obtain experimental information from the solar cell, encompassing the current and terminal voltage of the solar cell under varying loads. In this study, solar cell parameters were determined by using single-diode, double-diode, and triple-diode models. A predetermined algorithm incorporated the experimental voltage and current data into the respective models. The aim is to minimise the objective function, which represents the discrepancy between the actual and modelled values of the solar cell current.

1.3. Limitation of thesis

The limitation of this thesis can be summarised as followings:

- This study employed a limited set of models, specifically the 1-diode, 2-diode, and 3-diode models. In further investigations, additional models may be employed to investigate the potential of the proposed algorithm in different scenarios and applications. Doing this will provide a comprehensive list of limitations and enable its optimisation for specific use cases.
- The present study solely employed the commercial R.T.C France solar cell due to insufficient data. However, exploring other solar cell types may be beneficial to fully assess the proposed algorithm's effectiveness for estimation.
- Lack of Comparative Analysis: Although the thesis mentions comparing the simulation outcomes of various algorithms, it does not provide a comprehensive comparative analysis of these algorithms. A detailed evaluation and comparison of different optimisation algorithms would have clarified their strengths and weaknesses.

1.4. Thesis objectives

The fundamental objective of the thesis can be summarised as followings:

1. To create a model of solar cells that is accurate and trustworthy by using clever algorithms to choose the parameters, taking into account the non-linearity of the voltage-current connection, and making sure that the results of the model closely match the data that has been observed.

2. To overcome the difficulty of being trapped in local optima and offer trustworthy parameter estimates for solar cells, we propose an algorithm that exhibits excellent accuracy. This approach addresses the constraints of existing techniques.

3. To increase the performance and precision of solar cell models and make it possible to forecast system behaviour more precisely by using an upgraded particle swarm optimisation (PSO) technique for parameter estimation.

4. To assess and contrast the performance of various solar cell models, including those with one, two, and three diodes, based on root mean square error values, in order to identify the most appropriate model that demonstrates superior accuracy in capturing the intricate characteristics of solar cells and facilitates effective energy conversion.

1.5. Contribution of thesis

The main contribution is using an improved particle swarm optimisation algorithm to determine the best optimisation scenario.

1.6. Thesis motivation

The critical importance of utilising renewable energy sources in the foreseeable future and eliminating the reliance on non-renewable energy sources in the energy generation process constitutes a pivotal agenda for the progress of the global society. Solar power plants represent a fundamental method of generating energy from sustainable and environmentally friendly sources, offering a potential solution to the reliance on non-renewable fossil fuels in thermal power plants.

The utilisation of power plants is contingent upon various indicators, wherein the relative significance of each indicator may vary across different regions.

Conversely, the assimilation and substitution of solar systems within thermal power plants is a complex process that necessitates the assessment of numerous indicators and factors. Therefore, it is essential to employ a technique that can enhance the efficiency of substituting solar systems in thermal power stations while causing minimal disruption to the grid. Conversely, the utilisation of modelling techniques in such scenarios has the potential to enhance problem-solving efficiency and enable the quantification of relevant variables. On the flip side, the imperative of utilising renewable energy sources in the forthcoming years and phasing out non-renewable energy sources from the energy generation process is among the most crucial strategies for the progress of the global society. Solar energy is a fundamental method of generating energy from sustainable and environmentally friendly sources, which has the potential to mitigate the reliance on fossil fuels in thermal power generation. Consequently, the utilisation of these energy systems confers benefits across various societal sectors and organs. The assessment of its parameters motivates the present thesis.

1.7. Thesis Organization

This thesis is organised into five distinct sections.

- **Chapter one** Provides an overview of the thesis, embracing a comprehensive literature review, a clear problem statement, and a well-defined objective of the thesis.
- **Chapter two** Justify the theoretical background of photovoltaic system, electric models, single-diode model, double-diode model and triple diode-model where each of them is shortly explained.
- **Chapter three** Provides a comprehensive overview of the suggested algorithm’s technique.
- **Chapter four** Stands the outcomes of the Improved PSO algorithm as implemented through MATLAB simulation and indicates a comparative analysis between the proposed algorithm along with other existing algorithms.
- **Chapter Five** Review the conclusions and potential advantages of the proposed algorithm.

CHAPTER TWO

THEORETICAL BACKGROUND

Today, there is a growing interest in seeking various forms of renewable energy as a result of the obstacles placed on the use of fossil fuels in the production of energy. This interest is driven by the fact that the demand for energy consumption in the world is rising. The owners of fossil resources should be aware that extracting more from the reserves available now will result in fewer benefits in the future and will ultimately hasten the depletion of the resources. Thankfully, the majority of countries throughout the world have come to recognise the significance and function of energy resources, particularly renewable energy sources; as a result, a significant amount of research and fundamental investments have been made to use these resources. (Werner and Lazaro, 2023).More than nine percent of the total amount of energy that was utilised in the United States in 2011 came from sources that were considered to be renewable. The percentage of participation that each different kind of renewable energy has in this industry is displayed in Figure 1.

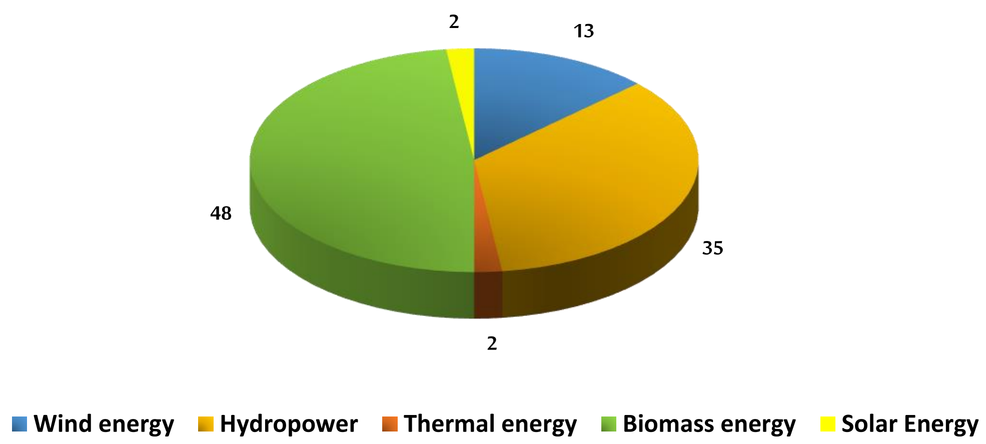

Figure 1. The percentage of participation of each renewable energy (Alemán-Nava et al., 2014)

Energy generated by the sun, the wind, the earth, or the sea costs nothing to operate. Solar cells, in particular, have found popularity across the world thanks to their convenient combination of low initial cost, long service life, and absence of environmental and acoustic impacts. Photovoltaic resources can be better utilised if the solar cell's specific model can be determined. Results from simulations will be closer to those produced in practice if the supplied model is as exact as possible.

Many models for solar cells have been given as solar energy research has advanced, but the single-diode and two-diode models have seen the most acceptance. (Ramos and Ringwood, 2016)(de Paulo and Porto, 2018)(Liao et al., 2021)(Koç, 2014)(Morim et al., 2016)(Chaurasiya et al., 2019)(Buratti and Fantozzi, 2010)(Shakya et al., 2023)(Mulenga et al., 2023)(Roose et al., 2022)(Nelson and Starcher, 2018)(Goggins et al., 2022).

2.1. Photovoltaic system

The electricity grid is powered by photovoltaic panels. In the photovoltaic system, solar cells transform sunlight into direct current power. DC and AC customers can get the power they require met by using the generated electricity (Tidjani and Chandra, 2012). Installers of solar systems in urban settings sometimes struggle to achieve ideal angles in practice, making this a significant difficulty when deciding where to place photovoltaic cells. The conversion of radiant energy into electrical energy without the need for mechanical devices is known as the photovoltaic phenomenon. The phenomenon is explained by the idea that electromagnetic radiation may be broken down into elementary particles. Photovoltaic systems are those that make use of this property. The three primary components of photovoltaic systems are:

• Solar Panels or modules that collect sunlight and transform it into usable electricity.

• The intermediate component or optimal power component manages and induces the electrical energy produced by photovoltaic systems to the consumer's requirements.

• Customer or electrical load contains all direct and alternating electrical consumers in proportion to their consumption.

Figure 2. depicts the horizontal solar radiation projection for the entire planet. It is obvious from this map that the areas between fifteen degrees and thirty-five degrees north latitude receive the greatest amount of sunlight. Approximately ninety per cent of the solar energy absorbed by the earth's surface occurs in the northern hemisphere when the sun is at its highest altitude. (Barbón et al., 2022)(Newbery et al., 2018)(Liu, 2018)(Q. Hassan, 2022).

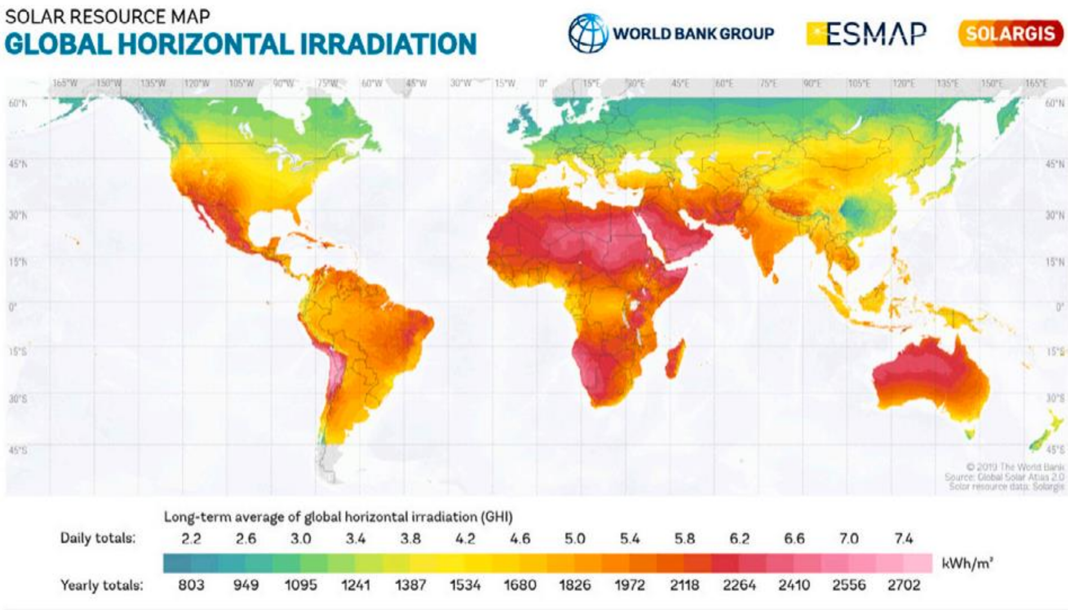

Figure 2. Map of global horizontal radiation around the world (Barbón et al., 2022)

The manufacturer typically lists the voltage and current ranges that each solar panel can produce in the product catalogue.Several panels can be linked in series or parallel to achieve the necessary conditions if the current or voltage of the intended panel does not match with other electrical equipment. However, generally, we align the panels in parallel to get the most power from them. Each panel's positive and negative outputs are wired to the other panel's positive and negative outputs, and then the entire system is wired to the charge controller, which regulates how quickly the batteries are charged. In addition, charge controllers feature an output so that, in the presence of sunshine, the necessary energy may be sent straight from the panel to the electrical devices. equipment can receive their desired energy directly through the panel (Shakeri et al., 2018).Solar heating systems, which are commonly utilised for commercial water heating, are another widespread application of solar energy.Villas, apartments, hotels, and various other facilities within both the residential and commercial sectors may simply heat their pools or drinking water with the help of solar energy, plus the financial return is fairly quick. With a yearly efficiency of 40%, a collector area of just 2 square metres may meet 80% of a Mediterranean family's hot water needs. The collection surface has to be greater (but still balanced) in less sunny regions. Although higher concentrations of solar energy will be needed, these systems can provide a significant portion of the need for space heating in buildings (Iskandar et al., 2019).

A particular field of research in solar energy is the precise modelling of solar cells through the development of optimum parameters. Part of this concept is determining the I-V (current versus voltage) relationship (Maniraj and Fathima, 2020).

Classical techniques and meta-heuristic algorithms are the two most common approaches to solving the modelling challenge of identifying unknown parameters.

2.2. Photovoltaic cell electrical model

Initial PV system costs are still relatively costly. Consequently, an accurate evaluation of the electrical characteristics is required for system design. Standard electric features of PV modules supplied by manufacturers include current at Maximum Power Point (MPP) I_{mp}, the voltage at MPP (V_{mp}), power at MPP (P_{max}), open-circuit voltage (V_{oc}), and short-circuit current (I_{sc}). These values are typically obtained from tests conducted under Standard Test Conditions (STCs), which involve a module temperature of 25 degrees Celsius and an irradiance of (1000 W/m^2) under spectral distributions of 1.5 air masses.

To determine the photovoltaic cell model, we need to identify the source's equivalent circuit. Several mathematical models have been created to characterise the nonlinear behaviour induced by semiconductor junctions. Different photovoltaic cell models can be identified from various sources from the manufacturing process and the parameters utilised for determining the voltage and current of the photovoltaic generator. A current source that makes light and an inverted diode have been employed to model an ideal solar cell. But the test results don't fit this model perfectly in real life. Therefore, we employ mathematical models that incorporate improvements over the original.Several mathematical approaches have been developed to represent the solar cell's nonlinear I-V curve. However, there are a few commonplace examples that can serve as recommendations which are (single, double, and triple). These models, which are the most often used ones for solar cells, have captured the interest of several academics as a result of their user-friendliness and high degree of accuracy. In consideration of this fact, we conducted this investigation utilising SDM, DDM, and TDM.

2.3. Ideal Single–Diode Model

An essential photovoltaic device is a PV cell, essentially a diode. It produces a reverse current when its p-n junction is illuminated. The current is known as Iph photogenerated current. In the darkness, the PV cell behaves like a diode; therefore, the Shockley diode equation typically expresses its dark I-V characteristics mathematically. Figure 2.3 depicts a theoretically ideal solar cell.

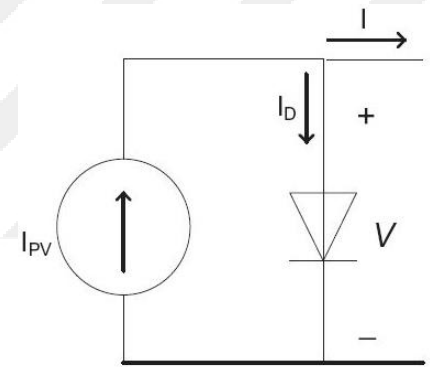

Figure 2. Ideal solar cell model (Askarzadeh and Rezazadeh, 2013)

2.4. Single diode model (SDM)

Due to its ease of use, the single-diode model (SDM) has attracted a large user base. Figure 4 depicts the equivalent circuit of the single-diode model. This model includes the following elements : (Nunes et el., 2018).

(1) A current source that responds to variations in cell/module temperature, solar irradiance, and material characteristics;

(2) A diode that operates in parallel with the current source and accounts for the effects of the p-n junction;

(3) The ohmic losses in the semiconductor are represented by the series resistor (R_s), and the leakage current is represented by the shunt resistor (R_{sh}).

Even though at first glance this model appears less accurate than the two-diode model, in practise, the minimum is more interested in reaching the final solution of this model due to its simplicity and speed. Following is the expression for the output current based on the equivalent circuit.

$$I_t = I_{ph} - I_d - I_{sh} \tag{2.1}$$

The following expression describes the model's terminal current relationship:

$$I_t = \mathrm{I_{ph}} - \mathrm{I_{sd}}\left[\exp\left(\frac{\mathrm{q(V_t - R_s I_t)}}{\mathrm{nkT}}\right) - 1\right] - \frac{\mathrm{V_t - R_s I_t}}{\mathrm{R_{sh}}}$$

(2.2)

I_t represents photovoltaic output current.

q as the electric charge, $\mathrm{I_{ph}}$ is the photogenerated current of the solar array, $\mathrm{I_{sd}}$ is the saturation current of the diodes, n is the ideality coefficient of the diode D, K is the Boltzmann constant, and T is the cell temperature.

In addition, five parameters are unknown and need to be acquired.{ $\mathrm{R_s}$, $\mathrm{R_{sh}}$, $\mathrm{I_{ph}}$, $\mathrm{I_{sd}}$ and n}

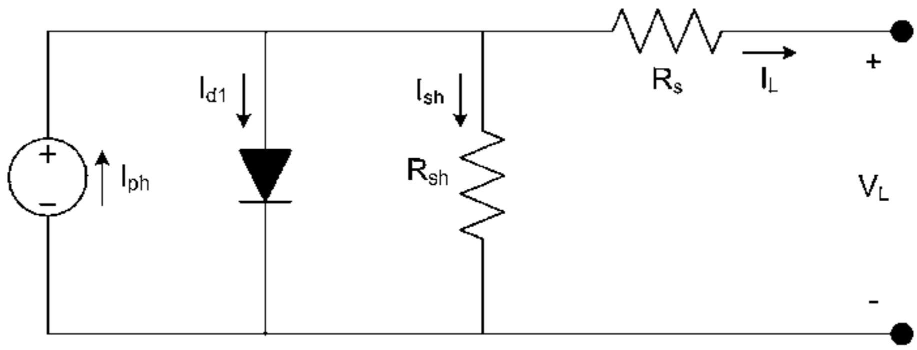

Figure 3. Single diode solar cell model (Mohammad Jamadi et el.,2016)

2.5. Double diode model (DDM)

Many researchers have devoted an enormous amount of time and energy to researching PV cells' dark characteristics. The 2-diode model, also known by the term DDM, includes a combination of two diodes connected in parallel to the current source. A representation of electricity of the double-diode model is seen in Figure 5. This model can more accurately represent the physical effects of the p–n junction, particularly at lower irradiance levels.

The current source Iph, which imitates the conversion of radiant energy into electric current, is part of this model. The series resistance Rs is the various resistances of the connection, the parallel diodes D_1 and D_2 represent the P-N junction model, and the parallel resistance R_{sh} reflects leakage resulting from side effects on the solar cell.

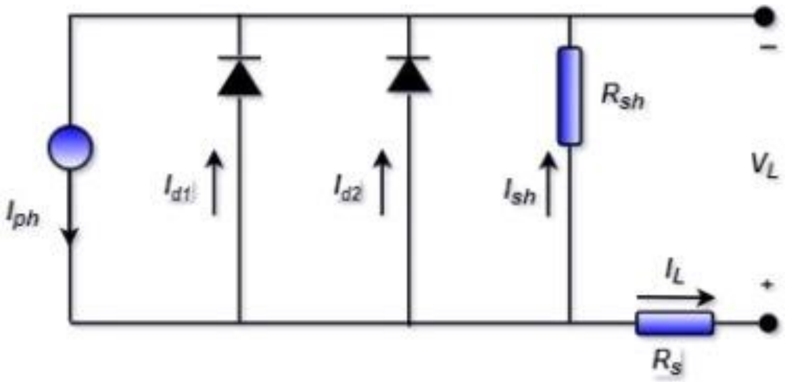

Figure 4. Photovoltaic cell model with two diodes (Naeijian et al., 2021).

According to the equivalent circuit of the double diode model,the current generated by the module is in the form of the following equation:

$$I_t = I_{ph} - I_{d1} - I_{d2} - I_{sh}$$
(2.3)

$$I_t = \mathrm{I_{ph}} - \mathrm{I_{sd1}}\left[\exp\left(\frac{\mathrm{q(V_t+R_sI_t)}}{\mathrm{n_1kT}}\right) - 1\right] - \mathrm{I_{sd2}}\left[\exp\left(\frac{\mathrm{q(V_t+R_sI_t)}}{\mathrm{n_2kT}}\right) - 1\right] - \frac{\mathrm{V_t+R_sI_t}}{\mathrm{R_{sh}}}$$
(2.4)

The equation above shows that the output current of the photovoltaic module is dependent on the radiant current, which in turn depends on solar radiation and the junction temperature of the module cells. Likewise, solar radiation and semiconductor junction temperature influence the amount of power a module can transmit.

Where, Vt is the terminal voltage, Rs is the series resistance and Rsh is the parallel resistance, Isd1 and Isd2 are the discharge and saturation currents of the first and second diodes. q Electric charge's coefficient, K Boltzmann's constant, the ideality coefficients of the diodes n1 and n2, and T the temperature.

Even though we have the test temperature and have measured the terminal output voltage and current, there are still seven other unknown parameters. Using an optimisation method and the experimental data, one may determine the value of the variable.The unknown parameters that should be obtained are 7 parameters { I_{ph},R_{sh}, R_s,I_{sd1},I_{sd2},n_1,n_2}

2.6. Three-diode model (TDM)

The three-diode model, sometimes referred to as the TDM, is a more realistic representation of reality than the two models that came before it. This is because the TDM takes into consideration the impact of leakage current and gain boundaries. Because of this problem, the model will almost certainly end up being more difficult to understand. According to this strategy, as shown in Figure 6. , three diodes are anticipated to be linked in parallel with the current source. This can be seen in the Figure.

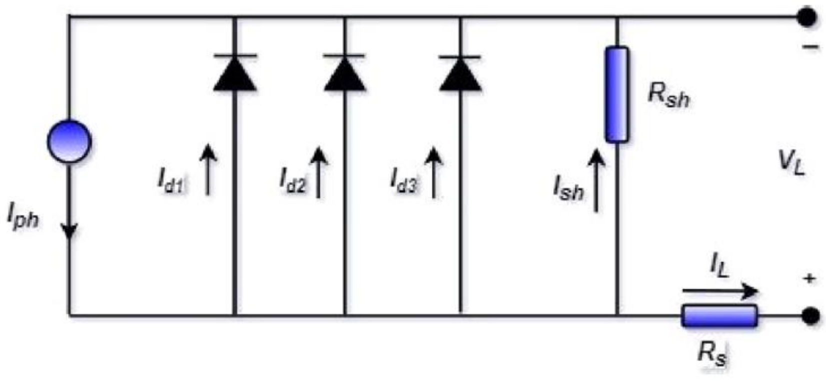

Figure 5. Equivalent circuit of TDM model (Naeijian et al., 2021)

Due to the equivalent circuit, the output current of this model can be expressed as follows:

$$I_L = I_{ph} - I_{d_1} - I_{d2} - I_{d3} - I_{sh} \tag{2.5}$$

Equation (2.5) can be written in the following form:

$$I_L = I_{ph} - I_{SD1}\left[\exp\left(\frac{q(V_L+I_LR_S)}{n_1kT}\right) - 1\right] - I_{SD2}\left[\exp\left(\frac{q(V_L+I_LR_S)}{n_2kT}\right) - 1\right] - I_{SD3}\left[\exp\left(\frac{q(V_L+I_LR_S)}{n_3kT}\right) - 1\right] - \frac{V_L+I_LR_S}{R_{sh}} \tag{2.6}$$

As a result of this, adding the third diode increases the overall number of unknown parameters by two, bringing the unknown parameters to nine. These parameters may be represented as a vector, which can be defined as:

$$x = [I_{ph}\ \ R_s\ \ R_{sh}\ \ I_{SD_1}\ I_{SD_2}\ I_{SD_3}\ n_1\ \ n_2\ \ n_3]$$

2.7. Photovoltaic (PV) system module model

As the output power of PV cells is limited at high voltage levels, PV modules are utilised as the primary components in large PV generation systems. researchers first developed a PV module model to predict the I-V characteristics before proceeding to model the entire system. In order to create a certain amount of voltage and current, the solar cells which comprise a photovoltaic (PV) module can be linked in series as well as parallel or both, depending on the design of the module. As demonstrated in Figure 7. (Naeijian et al.., 2021).

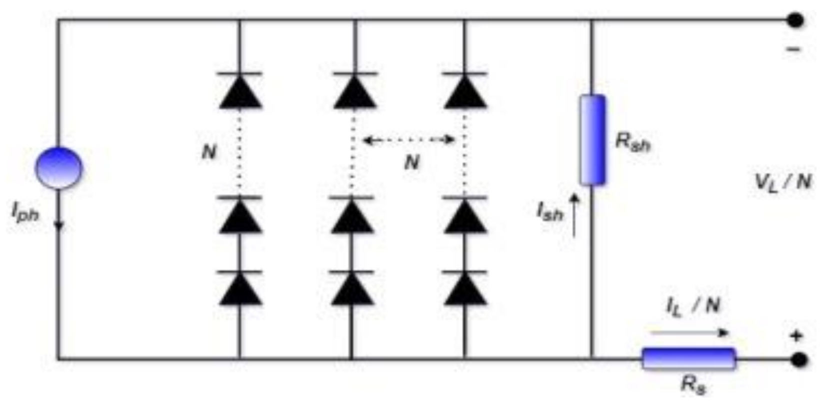

Figure 7. Equivalent circuit of PV Module Model (Naeijian et al., 2021)

The following equation can be used to calculate the output current of the panel (also known as a PV module):

$$I_L = I_{ph} - I_{SD} \times \left[\exp\left(\frac{q(V_L + I_L R_S)}{nkTN}\right) - 1\right] - \frac{V_L + NI_L R_S}{NR_{sh}}$$

(2.7)

Here N is the total number of cells contained within the PV module.

It is important to remember that every model has several unknown parameters, which must be stated with extreme caution.

This thesis solely focuses on the 1-DM, 2-DM, and 3-DM, since these are the most commonly employed in photovoltaic modelling and system control.

2.8. Photovoltaic module characteristics

Both the amount of sunlight hitting the cell and its operating temperature affect its performance. Figure 8 demonstrate the output characteristics of the photovoltaic module. When the radiation is steady and the temperature drops, the output power rises as a consequence. If the amount of radiation increases while the temperature remains unchanged, as shown in Figure 9, the output current and power will rise accordingly.

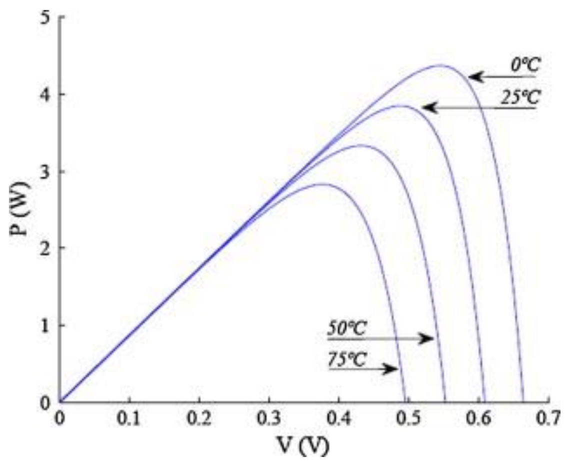

Figure 8. Characteristics of photovoltaic modules under different amount of temperatures and constant irradiation (Moharram et al., 2013)

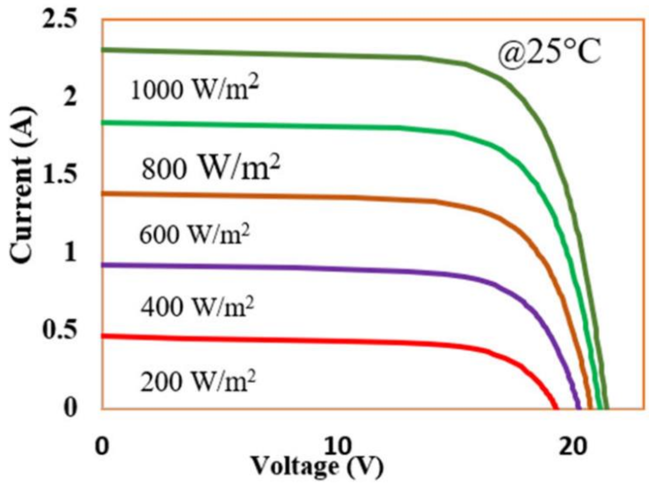

Figure 9. Characteristics of photovoltaic modules under various irradiations and constant temperature (Abdullahi et al., 2017).

The output characteristics of a photovoltaic module are important to understand its performance and efficiency. These graphs can help in determining maximum power point and the operating conditions for optimal energy production.

CHAPTER THREE

METHODOLOGY

3.1. An overview of the optimization method

As mentioned before, the goal of the optimisation methods is to identify a solution to the problem using some kind of algorithm. Finding the parameters of the SC's properties is our current challenge.The algorithm variables, which are the unknown parameters, can be separated into three models, 1-diode, 2-diodes, and 3-diodes models. 3.1, 3.2, and 3.3.

$$x = \begin{bmatrix} R_s & R_{sh} & I_{ph} & I_{sd} & n \end{bmatrix}$$

(3.1)

$$x = \begin{bmatrix} R_s & R_{sh} & I_{ph} & I_{sd1} & I_{sd2} & n_1 & n_2 \end{bmatrix}$$

(3.2)

$$x = \begin{bmatrix} R_s & R_{sh} & I_{ph} & I_{sd1} & I_{sd2} & I_{sd3} & n_1 & n_2 & n_3 \end{bmatrix}$$

(3.3)

Various upper and lower bounds for these variables have been proposed in various studies and reviews written on the topic. However, the following are the typical limits for solar cell characteristics. The Range of unknown solar cell parameters is shown in table 1.

Table 1. Range of unknown solar cell parameters (Rao and Patel, 2012)

Parameter	Lower	Upper
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	100
$I_{ph}(A)$	0	1
$I_{sd}(\mu A)$	0	1
N	1	2

3.2. The objective function

An optimisation challenge is defined to find the unidentified values of the cell/ PV module model's parameters.

As we mentioned previously, meta-heuristic methods can be used to overcome this problem. This optimisation problem must be resolved to obtain the unknown parameters, and it must be resolved so that the objective function is minimised. During optimisation, the desired function is typically determined by calculating the gap between actual and estimated current. This error is a problem which needs to be minimised to the maximum capacity that could possibly be. This thesis uses root mean square error (RMSE) as an objective function, which is commonly used in optimization problems. The mathematical expression for the objective function can be found in the equations below.

For the 1-diode model, relation (3.4) is utilised to derive the objective function, while relations (3.5) is for the two-DM, and (3.6) belongs to the three-DM:

$$f(V_t, I_t, x) = I_t - I_{ph} + I_{sd}\left[\exp\left(\frac{q(V_t+R_sI_t)}{nkT}\right) - 1\right] + \frac{V_t+R_sI_t}{R_{sh}} \quad (3.4)$$

$$f(V_t, I_t, x) = I_t - I_{ph} + I_{sd1}\left[\exp\left(\frac{q(V_t+R_sI_t)}{n_1kT}\right) - 1\right] + I_{sd2}\left[\exp\left(\frac{q(V_t+R_sI_t)}{n_2kT}\right) - 1\right] + \frac{V_t+R_sI_t}{R_{sh}} \quad (3.5)$$

$$f(V_t, I_t, x) = I_t - I_{ph} + I_{sd1}\left[\exp\left(\frac{q(V_t+R_sI_t)}{n_1kT}\right) - 1\right] + I_{sd2}\left[\exp\left(\frac{q(V_t+R_sI_t)}{n_2kT}\right) - 1\right] + I_{sd3}\left[\exp\left(\frac{q(V_t+R_sI_t}{n_3kT}\right) - 1\right] + \frac{V_t+R_sI_t}{R_{sh}} \quad (3.6)$$

Now, if we put in the value of voltage and current from the actual experiment and the values of the parameters determined by equations (3.4), (3.5), and (3.6) from the algorithm, we can see how much of an error there is between the two sets of results using the function $f(V_t, I_t, x)$.

The amount of electron charge, T, the temperature of the solar cell in Kelvin, and K is Boltzmann's constant, which is as follows (see table 2):

Table 2. Fixed values in solar cell relationships

q (c)	1.602e-19
T (^{o}k)	306
K	1.380650e-23

By utilising equations (3.4), (3.5), and (3.6), it is possible to obtain the corresponding error values for various experiments conducted on a range of solar cell parameters.

In other words, if we input a given value for the unknown solar cell parameters, there is a value of N for the number of practical tests (practical results), and we can assess whether the desired solution is desirable or not by utilising the square root of the sum of square errors. The relation of RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i(V_t, I_t, x))^2}$$

(3.7)

Where x is the solution vector, N is the number of tests performed or the number of samples output voltage and current of the solar cell. Generally, when a particular collection of solar cell parameter values exhibits low root mean square error (RMSE), it can be assumed that the algorithm-derived voltage and current values are more proximate to the corresponding voltage and current values of the solar cell terminal obtained through experimentation. The equation denoted as (3.7) may serve as a viable objective function, whereby the main goal of the algorithm is to minimise the said function.

3.3. Optimization algorithms

As previously stated, precise calculation of solar cell parameters necessitates the utilisation of intelligent algorithms that exhibit superior convergence accuracy.

The utilisation of particle swarm optimisation (PSO) algorithm has been employed for this particular objective. The Particle Swarm Optimisation (PSO) algorithm is a highly effective algorithm that yields superior results compared to alternative algorithms. The present study employs the Particle Swarm Optimisation (PSO) algorithm in its improved version to determine the unknown variables of the previously mentioned models. The algorithm exhibits several benefits, including but not limited to its notable precision and consistency, alongside its rapid convergence rate.

3.3.1. Particle Swarm Optimization Algorithm (PSO)

Historically, scholars have posited that flying creature movement and directional orientation are influenced by the celestial bodies of the moon, sun, and stars. However, investigation in this field shows that at first the birds are oriented at random, then, through interaction with each other, they settle on their main path, indicating group migration and a massive movement of birds.

In 1995, Eberhart and Kennedy were the first to describe the particle assembly algorithm. This approach is influenced by the collective locomotion of fish and the seasonal movement of avian species. The algorithm was employed to uncover the underlying patterns that regulate the coordinated flight of avian species and their unexpected alterations in direction. The particle assembly algorithm exhibits diverse applications, including but not limited to function optimisation, training of artificial neural networks, implementation of fuzzy control systems, automation of systems, and utilisation of image processing techniques, among others.

The Particle Swarm optimisation technique is founded on the algorithm delineated in the works of Kennedy and Eberhart (1995), with adaptations proposed by Mezura-Montes and Pedersen (2010) and Coello Coello (2011).

The particle swarm algorithm commences by generating the initial particles and assigning them with initial velocities. The objective function is evaluated at every particle position, leading to the identification of the optimal location and the best function value. It chooses new velocities by considering the current velocity, the optimal positions of the particles, and the optimal positions of their neighbours.

Particle locations, velocities, and neighbours will then be updated in a series of iterations. Particles' new locations are the sum of their current positions and their velocities, which are adjusted so that they never leave the defined region. The algorithm will proceed to carry out iterations until it reaches a stopping criterion.

3.3.2. Particle Swarm Optimization Algorithm for feature selection

To overcome the difficulty of interpreting visuals in animations created using a computer that was intended to be similar to natural occurrences, one solution that was employed was the hypothesis of utilising several agents (particles, populations) who interact with simple natural techniques to make supposedly complex disability behaviours. This solution was one of the solutions that were employed to overcome the challenge of interpreting visuals in computer animations that were intended to be similar to natural occurrences. This action was taken in an attempt to find a solution to the issue. Rios, who is widely regarded as one of the industry's early pioneers, utilised particle devices as part of his work at Lacasse Film. This was one of the company's many groundbreaking innovations. These devices, each of which included several components, collaborated to produce a fuzzy function. The particle machine produced a series of moving points in a random sequence, and these points frequently began their motion in positions that had been previously specified. A handful of arbitrary parameters were responsible for the iterative adjustments that were made to the velocity vectors. Then, after assuming its new velocity vector, each particle left its original place and moved on to the next point in the series in order.

To successfully go to this new location, a specific angle must be adopted to give the impression that the transition occurred naturally. These kinds of systems went through an exhaustive development process to establish social implications and the actual interactions of graphical environments. Some animations required more dynamic group behaviour than could be achieved with individual particles. An instance of this phenomenon can be observed in the context of avian communities. Creating a file that initiated member behaviour was feasibleThe creation of a file that triggered member behaviour was possible, albeit requiring a significant amount of meticulous effort. In addition, it was difficult to generate responses that appeared natural. Reynolds developed his higher-level group algorithm by using Rios particle system as a basis for his work.

It takes into account the particles' previous motion and supplemented it with elements like inclinations, position identification, and data correspondence. The additional actions exhibited by the group members complied with the fundamental guidelines prescribed for group membership, including but not limited to avoidance of collisions, adjustment of the velocity vector by other members, and maintenance of a superior position relative to other members.Even though the development of these essential models raised individual (members') intelligence, it also removed the need for them to log their routes.Increasing the amount of liberty that individuals have, however, can lead to issues such as incompatibility.

To find a solution to the issue, Reynolds made a move that prioritized his dominance over other options. On the other hand, the decision may be wholly arbitrary and open to interpretation. We may think about using a gadget in which each individual particle is aware of the movements being carried out by the entire population as an example of a straightforward implementation. In this scenario, the problem can become extremely difficult to solve, or it might even become impossible, as a result of a growth in the number of population particles.

Reynolds suggested using the neighborhood system as a solution to this issue. This approach, which is utilized in nature due to the limited visibility of members, is also utilized by humans. However, current study reveals that using this strategy modifies the behavior of the impaired population. By taking into account people's social behaviors, Kennedy and Haharat hoped to make Reynolds' model more comprehensive. The most essential thing they did was change the simple aim of finding a nest that Hepner and Greenander had originally established into an algorithm that was built from an algorithm for a periodic group to the more realistic goal of locating food. Because of this, academics started applying this approach to mathematical issues that needed to be clarified. The objective function of the problem is viewed as a function of the level of fitness possessed by individual members of the population by these methods. (Which are now referred to as representative due to the fact that they are more general than the bird model). By eliminating the variables that were both ineffective and unnecessary, it was possible to produce a model that was both more effective and simpler (Fernandez-Viagas et al., 2017)(Beni, 2020)(Nguyen et al., 2020)(Niu et al., 2021)(Cho, 2017).

The optimum solution for the entire swarm and for each individual particle is the goals of PSO, which changes particle position and velocity over time. The equations below are used to update the particle positions $x_i(t)$ and velocity $v_i(t)$, uniform random variables r_1 and r_2 between in the range of [0 -1] are used to generate the random variation. Where w is the inertia weight, c_1 is the cognitive learning factor, c_2 is the social learning constant, Particle i has never achieved a better position than p^i_{best}, and any member of the population has never achieved a better position than g_{best}. To calculate and update the next particle position $x_{i,(t+1)}$ and velocity $v_{i,(t+1)}$ we use the following equations:

$$v_{i,(t+1)} = w\, v_i(t) + c_1 r_1 (p_{ibest}(t) - x_i(t)) + c_2 r_2 (g_{best}(t) - x_i(t))$$
(3.8)

$$x_{i,(t+1)} = x_i(t) + v_{i,(t+1)}$$
(3.9)

In figure 3.1, best local solution P^i , and the best global solution P_g , (v_i^k) is the velocity of particle i on iteration k,it is shown how particle location and velocity are updated. Particle swarms are significantly more quickly and effectively converge to similar solutions than genetic algorithms, according to considerable research done by Hassan et al. (R. Hassan et al.., 2005). Particle swarm parameters are shown in Table 3.

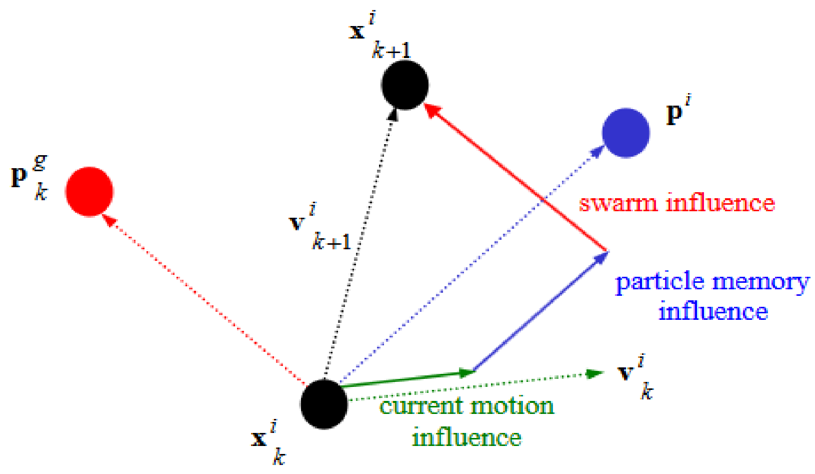

Figure 10. Velocity and Position Updates in PSO Diagram (R. Hassan et al., 2005)

Table 3. The parameters of PSO

Parameter	Value
Maximum number of iterations	200*Nvar
Population size of the swarm	[10, 30, 50, 70, 90, 100]
Searching area	[lb ub]
Dimension of the problem (Nvar)	[5, 7, 9]

The constriction parameter depended on lower band and upper band of the searching area. In this thesis, the lower band and upper band has been shown in table 3.

Maximum number of iterations in proposed method based on the PSO has been selected as the variable number. In this thesis, three scenarios have been implemented single diode model that selected as 200*Nvar, which the Nvar is the number of the variable that has been founded by the algorithm. For 1- diode model the maximum iteration has been selected as 1000. Also, for the 2- diode model and 3- diode model it is 1400 and 1800, respectively.

The equation of the PSO algorithm is presents below (Too et al., 2019):

$$v_i^d(t+1) = wv_i^d(t) + c_1r_1(\text{ pbest }_i^d(t) - x_i^d(t)) + c_2r_2(\text{ gbest }^d(t) - x_i^d(t)) \tag{3.10}$$

During each cycle, each particle receives two "best" values as an upgrade. Where, v stands for velocity, which is limited by the values of w_{max} and w_{min}, w for inertia weight, and x for the solution. As we continue on, t stands for the quantity of irritants, i for the population's order of practicality, and d for the size of the search field. The acceleration factors (c1, c2) and two independent random values (r1, r2) with range [0, 1]. Particle swarm optimisation records the global solution, which is the best value so far by any particle for the entire population, whereas pbest denotes the personal best solution (the best answer so far).

After that, as shown in the following equation, velocity is converted to a probability value:

$$s(v_i^d(t+1)) = \frac{1}{1+\exp(-v_i^d(t+1))} \tag{3.11}$$

Practical position and $pbest$ with $gbest$ are converted to the following equations:

$$x_i^d(t+1) = \begin{cases} and1, & andand \text{ if rand } < S(v_i^d(t+1)) \\ and0, & andand \text{ otherwise} \end{cases}$$

(3.12)

Where $rand$ is a random number between 0 and 1.

$$\text{pbest }_i(t+1) = \begin{cases} andx_i(t+1), & andand \text{ if } F(x_i(t+1)) < F(\text{ pbest }_i(t)) \\ and \text{ pbest }_i(t), & andand \text{ otherwise} \end{cases}$$

(3.13)

$$g \text{ best } (t+1) = \begin{cases} andp_{\text{best }i}(t+1), \text{ if } F(\text{ pbest }_i(t+1)) < F(\text{ gbest } (t)) \\ and\text{gbest}(t), \text{ otherwise} \end{cases}$$

(3.14)

Where F the fitness function.

$$w = w_{max} - (w_{max} - w_{min})\left(\frac{t}{T_{max}}\right) \tag{3.15}$$

Where w is the inertia weight , w_{max} and w_{min} are upper and lower bounds of w .

3.3.3. The proposed algorithm

In this thesis, we used the improved Parameter estimation of solar cells and modules using an improved version of the particle swarm optimization algorithm. To accelerate the normal PSO method's optimization process, an enhanced PSO algorithm variation was developed in (Wu and Song, 2021)(Li and Coster, 2022). To maximize accuracy and diversify the population, the suggested algorithm combined the core ideology of the genetic algorithm and dynamic parameters.

Each iteration involves splitting the superior particles and removing the inferior ones. That is, in each iteration, the fitness values of the particles are ranked from high to low, and particles with top 10 percent fitness values as "superior particles" are taken. Then, each superior particle is split into two particles with the identical velocities and locations, and particles with the poorest 10 percent fitness scores are removed to keep the swarm in a consistent size. The fundamental tenet of the genetic algorithm is adopted in this improvement: those with greater fitness levels will generate more offspring. In optimization methods, the splitting process is typically referred to as individual cloning (Wu and Song, 2021)(Li and Coster, 2022). The algorithm employs dynamic parameters c1 and c2 which can be determined and updated from the following equations:

$$c_1 = (c_{upper} - c_{low}) \times \frac{max\ iter - iter}{max\ iter} + c_{low} \tag{3.16}$$

$$c_2 = (c_{upper} - c_{low}) \times \frac{iter}{max\ iter} + c_{low} \tag{3.17}$$

In the equations above, iter is the current iterations number, maxiter is maximum number of iterations, c_{upper} and c_{low} are upper and lower limits of the learning factors.

Also we can calculate and update the inertia weight from the following equation:

$$\omega = (\omega 1 - \omega 2) \times \frac{max\ iter - iter}{max\ iter} + \omega 2 \tag{3.18}$$

To update the position and velocity we use the equations below:

$$v_{i(t+1)} = \omega \times v_{i(t)} + c_1\, r_1 \left(p_{ibest} - x_{i(t)}\right) + c_2 r_2 \left(g_{best} - x_{i(t)}\right) \tag{3.19}$$

$$x_{i,(t+1)} = x_i(t) + v_{i,(t+1)} \tag{3.20}$$

Initially, bird individuals exhibit a substantial cognitive learning capacity and a relatively limited propensity for social learning, mainly relying on personal experience for searching. Over time, bird individuals tend to increasingly depend on social knowledge for their foraging behaviour as they acquire knowledge from the bird population. Furthermore, the decreasing impact of inertia velocity can be observed as time progresses, owing to the particles' incorporation of cognitive and social learning during their search. Consequently, the reliance of the particles on their knowledge exceeds that of inertia.

After implementing the enhancements above, improved Particle Swarm Optimisation (PSO) algorithms are presented as follows. Following the standard notations in the relevant literature, we denote the variables $x_i(t)$, $v_i(t)$, $p_{ibest}(t)$ and $g_{best}(t)$ in Formulas (3.19) and (3.20) as x_i, v_i, p_{ibest} and g_{best}, respectively, to avoid any ambiguity.

Figure 11. depicts the algorithm's flowchart, which demonstrates how the algorithm works.

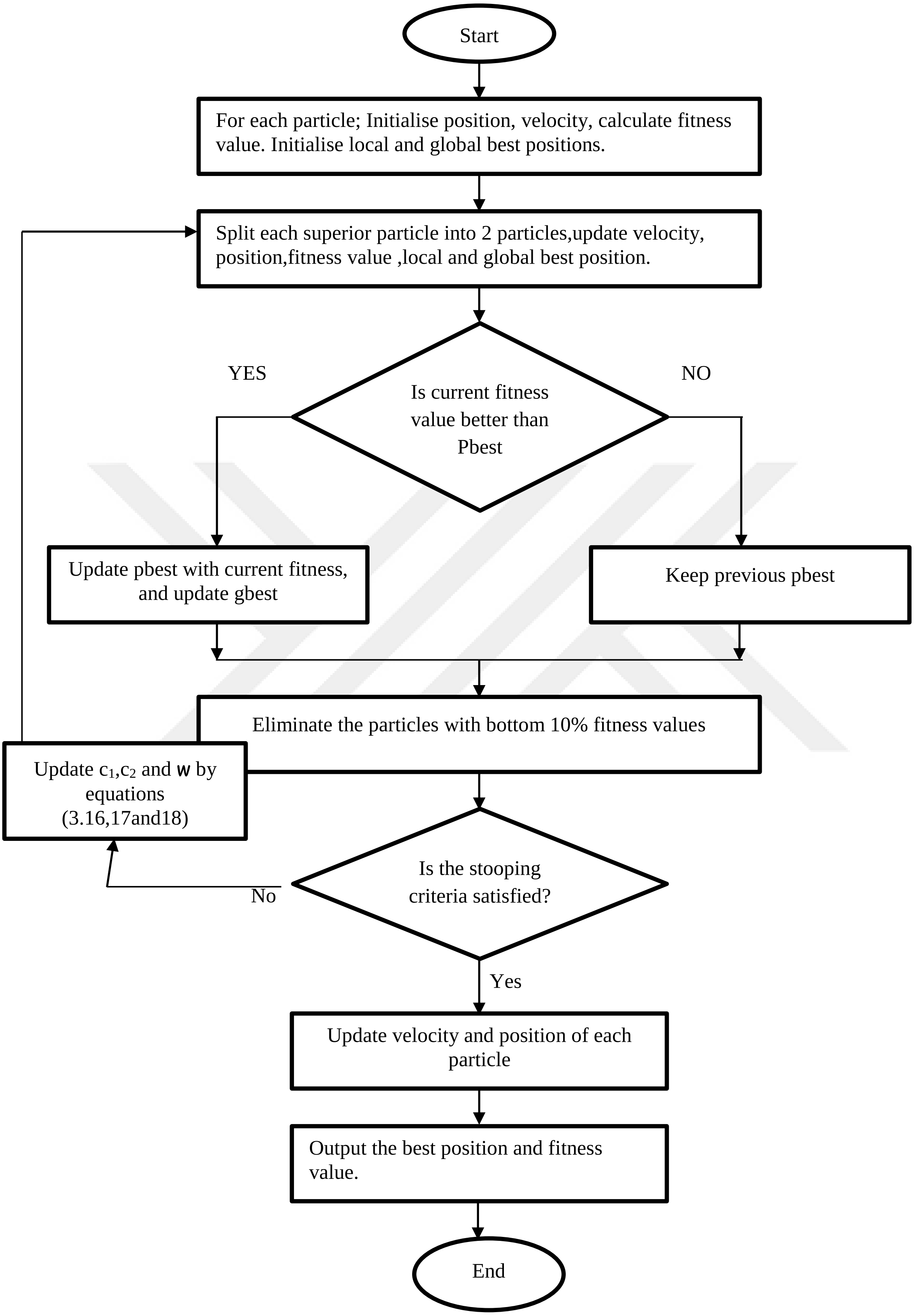

Figure 11. Improved PSO flowchart

3.4. Initialization

Particle swarm's default settings cause it to generate particles at random, uniformly, and within limitations. If there is an unlimited component, the particle swarm will generate particles with a random uniform distribution ranging from –1000 to 1000. Once you only specify a single bound, the particle swarm will modify the creation so that the bound serves as the endpoint, and the interval will be 2000 wide. The expression x(i) denotes the position of particle i, represented as a row vector comprising nvars elements. The duration of the initial swarm can be established by means of the InitialSwarmSpan parameter. Similarly, the particle swarm algorithm initiates particle velocities v by randomly homogeneously generating them within the range of [-r, r], Where r is a vector representing initial ranges. The minimum value of the expression min(ub(k)- lb(k), InitialSwarmSpan(k)) represents the range of the component k. Particle swarm analyses each particle individually by evaluating the objective function. It presents a record of the present position p(i) of each particle. In successive iterations, p(i) the location of the optimal objective function discovered by particle i will be determined. And the best particle is b, which may be calculated as follows: b = minimum fun(p(i)). d refers to the position at which b equals fun(d).

To begin, a particle swarm uses N, a minimal practicable neighbourhood size. The following is the formula for determining NeighborhoodSize: max(2,floor(SwarmSize*MinNeighborsFraction)).

If the inertia range parameter is positive , the Particle swarm initialises the inertia to W = max(InertiaRange) when it first begins, but if it is negative, it sets the inertia to W = min(InertiaRange).

When starting up, the particle swarm algorithm initialises the stall counter to zero. Setting the variable y1 to equal SelfAdjustmentWeight and setting the variable y2 to equal SocialAdjustmentWeight will be expected to simplify the process of notation. SelfAdjustmentWeight and SocialAdjustmentWeight are two interchangeable alternatives. The pseudo-code for the improved PSO is illustrated in Figure 3.3.

Algorithm: Pseudo code of improved PSO algorithm

Initialisation

1. *Set each n particle's initial position (xi) and velocity (vi) at random starting points in the associated search space.*
2. *Calculate the fitness value of every particle f(xi) by using the objective function.*
3. *Assess the local best position (p_{ibest}) and the global best position (g_{best}).*
4. *For r1 and r2 uniformly (0,1) distributed random vectors of length nvars, update the velocity equation*

$$v_{i(t+1)} = \omega \times v_{i(t)} + c_1\, r_1\big(p_{ibest} - x_{i(t)}\big) + c_2 r_2\big(g_{best} - x_{i(t)}\big)$$

Updating

This update uses a weighted sum of:

a. *The previous velocity v*
b. *The difference between the current position and the best position the particle has seen pibest - xi(t)*
c. *The difference between the current position and the best position in the current neighbourhood gbest – xi(t)*

1. *Sort particles by fitness values in descending order and select the top 10 percent as "superior particles". Split each superior particle into two particles with identical velocities and positions. Then, apply Formula (3.10) to update the velocity of the particles*
2. *Based on the velocity, update the position of particles with Formula (3.11).*
3. *Enforce the bounds. If any component of x is outside a bound, set it equal to that bound. For those components that were just set to a bound, if the velocity v of that component points outside the bound, set that velocity component to zero.*
4. *Update the fitness value f (xi).*
5. *Update the local and global best positions pibest and gbest. Then update the fitness values of pibest and gbest.*
6. *Remove particles with the lowest 10% fitness values.*
7. *Evaluate the objective function f = fun(x).*
8. *If stopping criteria is satisfied, output the gbest and fitness value (denoted by f (gbest). If not, update c1, c2 and ω by formulas (3.16)(3.17)(3.18) and repeat the update process.*

Figure 12. The pseudo code for the improved PSO

CHAPTER FOUR

RESULTS AND DISCUSSION

In this chapter, we take a look at the results that were acquired from the simulations that were carried out in the MATLAB software environment. After modelling the solar cell for this purpose, the PSO algorithm was used to identify the ideal parameters of the solar cell and the acquired results were compared with the results of other optimization methods. This was done to accomplish the previously mentioned objective.

4.1. Specifications of the solar cell used

The type of solar cell that was employed in this thesis is a typical model that is employed in solar cell modelling studies. This commercial (R.T.C France) silicon solar cell model has a diameter of 57 millimetres (AlHajri et al., 2012). The outcomes of the practical test include the voltage and current of the solar cell terminal that was achieved in the radiation that was 1000 W/m2 and at a temperature of 33 ^oC. Table 4. illustrates the voltage and current that are present at the desired solar cell terminal in each of the 26 possible states. It has been summed up.

Table 4. Results obtained from practical tests

No	I_t (Amper)	V_t (Volt)
1	0.764	-0.2057
2	0.762	-0.1291
3	0.7605	-0.0588
4	0.7605	0.0057
5	0.76	0.0646
6	0.759	0.1185
7	0.757	0.1678
8	0.757	0.2132
9	0.7555	0.2545
10	0.754	0.2924
11	0.7505	0.3269
12	0.7465	0.3585
13	0.7385	0.3873
14	0.728	0.4137

15	0.7065	0.4373
16	0.6755	0.459
17	0.632	0.4784
18	0.573	0.496
19	0.499	0.5119
20	0.413	0.5265
21	0.3165	0.5398
22	0.212	0.5521
23	0.1035	0.5633
24	-0.01	0.5736
25	-0.123	0.5833
26	-0.21	0.59

4.2. Optimization results for single diode model

The results of running simulations on the model of a single-diode solar cell are reported in this part of the work. The algorithm has been run through the test phase for the single-diode model six times, and the results generated from the simulation have been presented in Table 5. for the sake of simplicity.

Table 5. Comparing the results of six times of implementation the Improved PSO algorithm for the single diode solar cell model

No. of Particles	Iph	Io	Rsh	Rs	Ns	RMSE
PSO = 10	**0.7608**	**0.3106**	**52.8804**	**0.036547**	**1.4772**	**7.7299e-04**
PSO = 30	0.7608	0.3105	52.8905	0.036547	1.4773	7.7299e-04
PSO = 50	0.7608	0.3106	52.8867	0.036549	1.4773	7.7299e-04
PSO = 70	0.7608	0.3107	52.9163	0.036547	1.4773	7.7299e-04
PSO = 90	0.7608	0.3107	52.9084	0.03655	1.4773	7.7299e-04
PSO = 100	0.7608	0.3104	52.8917	0.036547	1.4773	7.7299e-04

As indicated in Table5., the Root Mean Square Error achieves a value of (7.7299e-04) , which represents the algorithm's minimum error and serves as its outcome. This value is then compared to the results of other algorithms, as presented in Table 6. It is noteworthy that the outcomes of alternative algorithms have been sourced from the literature, specifically from (AlHajri et al., 2012)(Fan et al., 2022)(Naeijian et al., 2021).

The present section conducts tests on the RTC France cells dataset to evaluate the efficacy of the proposed algorithm for detecting SDM. Table 5. displays the parameter outcomes and root mean square error (RMSE) obtained by each method. Figure 13 and Figure 14. depict the I-V and P-V fitting curves of the measured data in comparison to the estimated data, respectively.Table 6. demonstrates that the RMSE of the suggested algorithm, which is (7.7299e-04) , is the lowest of any of the other algorithms' RMSE values.

The Whippy Harris Hawks Optimisation algorithm (WHHO), Enhanced Harris Hawk Optimisation (EHHO), Performance-Guided JAYA algorithm (PGAYA), and Improved JAYA optimisation (IJAYA) exhibit identical root mean square error values, specifically (9.8602e-04). The Cuckoo search (CS) algorithm, particle swarm algorithm (PSO), and Genetic algorithm (GA) exhibit inferior performance, as evidenced by their respective values of (1.1085E-03), (1.38e-03), and (1.8704e-02). The results of independent testing shown in Table 4.3 demonstrate that the suggested algorithm beats the other approaches. As can be shown in Figures 13. and 14., the I-V and P-V curves between the estimated date of the proposed algorithm-optimised SDM and the measured data are well-suited.

Table 6. Comparing the results of different algorithms in the single diode solar cell model (Naeijian et al., 2021) ; (Y.Fan, et al., 2022)

Results	I_{ph} (A)	I_{sd} (μA)	R_S (Ω)	R_{sh} (Ω)	N	RMSE
Improved PSO	**0.7608**	**0.3103**	**0.0365**	**52.8729**	**1.4772**	**7.7299 e-04**
PSO	0.76054	0.41228	0.035409	62.253	1.5062	1.38e-03
WHHO	0.7607755	0.3230	0.03637710	53.71867407	1.48110808	9.8602 e−04
EHHO	0.760775	0.323	0.036375	53.74282	1.481238	9.8602e−04
PGJAYA	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602e−04
IJAYA	0.7608	0.3228	0.0364	53.7595	1.4811	9.8603e−04
GOTLBO	0.7608	0.3297	0.0363	53.3664	1.4833	9.8856e−04
GA	0.7619	0.8087	0.0299	42.3729	1.5751	1.8704e−02
CS	0.76040	0.34421	0.036320	57.238	1.4877	1.1085e−03

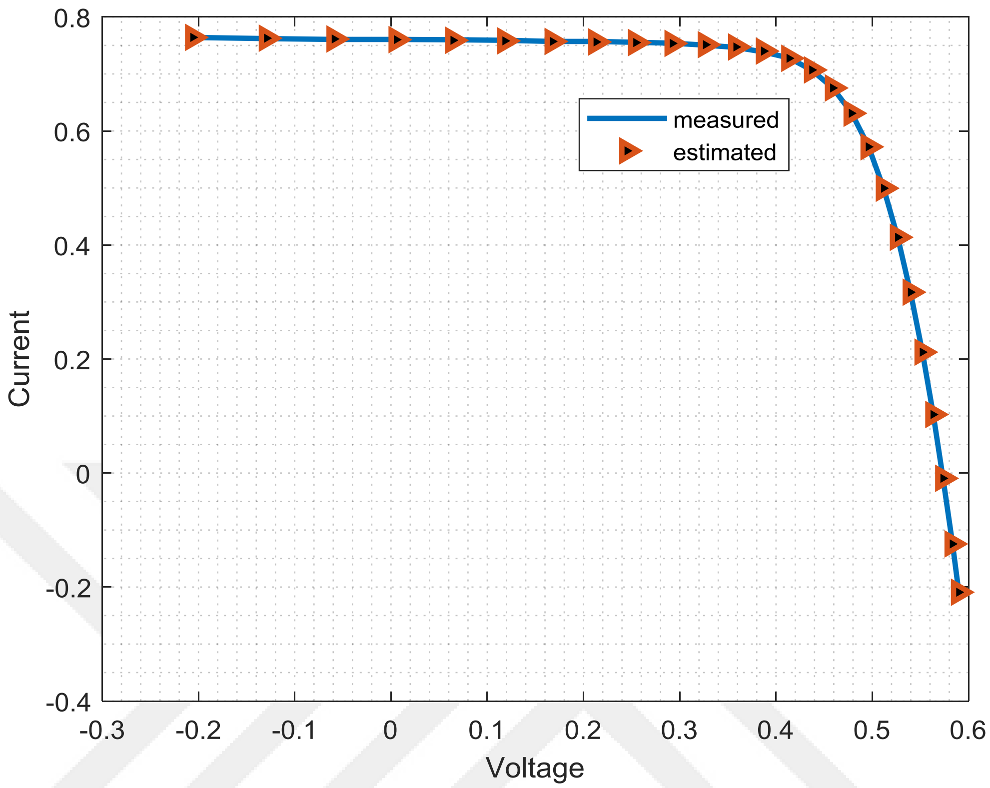

Figure 13. I-V characteristic curve

The I-V characteristic's experimental findings are depicted by the blue curve in Figure 13, while the Improved PSO algorithm's output is depicted by the brown triangle.

The P-V characteristic curve is shown in Figure 14.

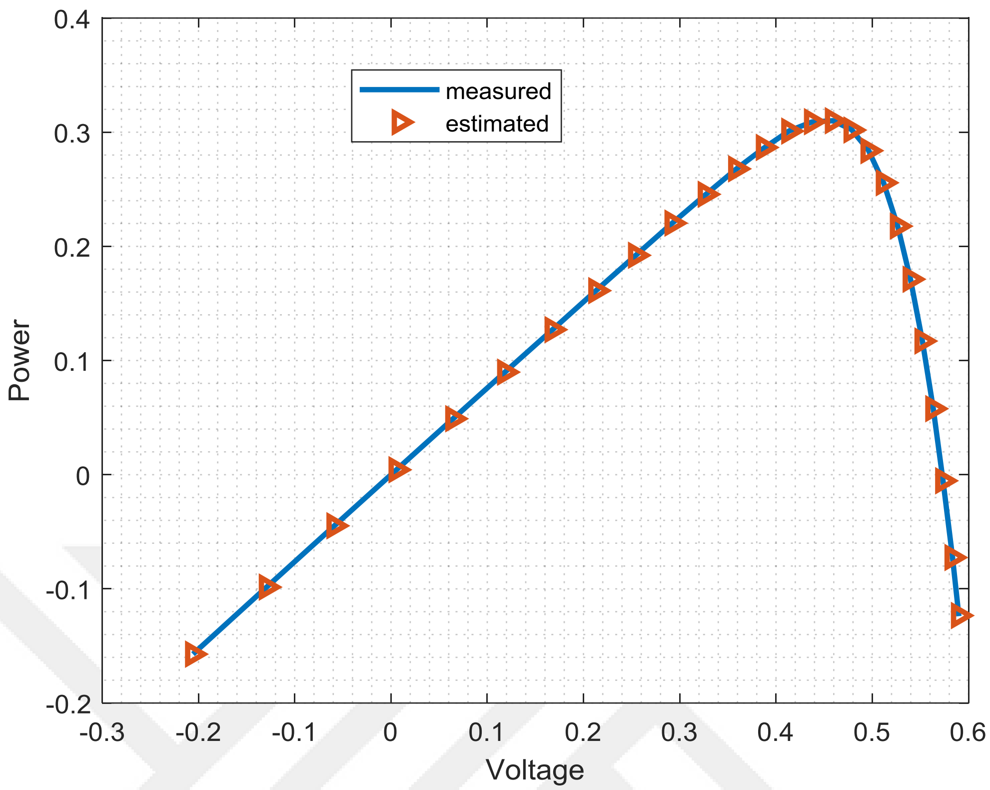

Figure 14. P-V characteristic curve

Figure 14. displays the P-V characteristic experimental findings as a blue curve and the I-PSO algorithm results as a brown triangle.Table 7. presents a comparison of the outcomes obtained from running the single-diode model algorithm 10 times at PSO = 10.

Table 7. Comparison of the results of 10 times of running the algorithm for the single-diode solar cell model

First 5 runs					
Results	Run 1	Run 2	Run 3	Run 4	Run 5
Iph	0.760787963	0.760788056	0.760788537	0.760788613	0.760789725
Isd	0.310683889	0.310684044	0.310465454	0.310364064	0.310403324
Rsh	52.890785	52.8356559	52.882040	52.862750918	52.88706223
Rs	0.036546862	0.036546867	0.03654989	0.036551305	0.036550386

n	1.477269366	1.477269425	1.477198922	1.477166178	1.477179173
RMSE	**0.000772986**	**0.000772986**	**0.000772987**	**0.000772987**	**0.0007729857**
second 5 runs					
Results	**Run 6**	**Run 7**	**Run 8**	**Run 9**	**Run 10**
Iph	0.760787963	0.760788056	0.760788537	0.760788613	0.760789725
Isd	0.310683889	0.310684044	0.310465454	0.310364064	0.310403324
Rsh	52.88908221	52.8883773	52.87012816	52.86325349	52.8500055
Rs	0.036546862	0.036546867	0.03654989	0.036551305	0.036550386
n	1.477269366	1.477269425	1.477198922	1.477166178	1.477179173
RMSE	**0.000772986**	**0.0007729879**	**0.0007729856**	**0.0007729856**	**0.000772986**

4.3. Optimization results for the two-diode model

The algorithm has been implemented ten times for each different number of the PSO. The results obtained from the simulation are summarized in Table 8., and these results are after ten times of running the algorithm and selecting the best solution.

Table 8. Comparing the results of ten times of running the PSO algorithm for the two- diode solar cell model

No. of Particles	**Iph**	**Isd1**	**Isd2**	**Rsh**	**Rs**	**Ns1**	**Ns2**	**RMSE**
PSO = 10	**0.7608**	**0.4566**	**0.139914996**	**59.99444917**	**0.035885383**	**1.530716822**	**1.522258257**	**0.000728001**
PSO = 30	0.7608	0.2146	0.499099292	61.11847826	0.035644282	1.542062453	1.531168889	0.000751751
PSO = 50	0.7607	0.3251	0.072526496	70.50016086	0.035381919	1.553221316	1.557678629	0.000700233
PSO = 70	0.7607	0.2550	0.241650766	66.77534882	0.035168328	1.551233306	1.546478509	0.000720182
PSO = 90	0.7607	0.4150	0.151778466	64.05625778	0.035381204	1.61204539	1.543412873	0.000713172
PSO = 100	0.7607	1.0000	0.274801444	67.95732341	0.035446767	1.578768093	1.572486038	**0.00069661**

To confirm the accuracy of the Improved PSO optimization algorithm, the program has been executed ten times of running, and the results of running are given in Table 9. By comparing the response of these executions, it can be seen that the changes in the objective function are very small. This proves that the proper performance of the algorithm was not random.

Table 9. Comparison of the results of 10 times of running the algorithm for the two-diode solar cell model

First 5 runs					
Results	Run 1	Run 2	Run 3	Run 4	Run 5
Iph	0.7608	0.7608	0.7606	0.7600	0.7611
Isd1	0.2688	0.1639	0.3386	0.1883	0.2598
Isd2	0.1982	0.3293	0.1222	0.2537	0.1464
Rsh	57.4363	56.8870	61.0618	77.7590	48.0595
Rs	0.0357	0.0359	0.0357	0.0352	0.0372
n1	1.6150	1.4459	1.5760	1.5268	1.6490
n2	1.4607	1.6268	1.4414	1.5044	1.4238
RMSE	0.00069661	0.0014	0.00091667	0.00075928	0.0012
Second 5 runs					
Results	Run 6	Run 7	Run 8	Run 9	Run 10
Iph	0.7608	0.7609	0.7608	0.7608	0.7617
Isd1	0.2102	0.0909	0.2512	0.2054	0.2038
Isd2	0.1601	0.3072	0.2745	0.2715	0.3059
Rsh	54.6517	55.9834	56.9575	58.7942	44.8078
Rs	0.0363	0.0354	0.0358	0.0354	0.0360
n1	1.5569	1.5322	1.7420	1.4687	1.4517
n2	1.4497	14954	1.4739	1.6011	1.6959
RMSE	0.00074913	0.00071858	0.00099813	0.0009786	0.00076038

According to Table 9. , the implementation which has a low amount of pso number with a low error is considered as the result of the algorithm and we compare it with the answer of other algorithms in Table 10. It should be noted that the results of other algorithms are taken from reference (AlHajri et al., 2012).

Table 10. Comparing the results of different algorithms in the two-diode solar cell model

Results	$R_s(\Omega)$	$R_{sh}(\Omega)$	$I_{ph}(A)$	$I_{sd1}(\mu A)$	$I_{sd2}(\mu A)$	N_{s1}	N_{s2}	RMSE
IPSO	**0.0359**	**57.2398**	**0.7608**	**0.2038**	**0.3059**	**1.5564**	**1.5173**	**7.28000e-04**
GOTLBO	0.0365	53.4058	0.7608	0.13894	0.26209	1.7254	1.4658	9.8742 e−04
PSO	0.03651	53.173	0.7608	0.30290	0.088734	1.4753	2	9.8638 e−04
IJAYA	0.0376	77.8519	0.7601	0.00504	0.75094	1.2186	1.6247	9.8293 e−04
PGJAYA	0.0368	55.8135	0.7608	0.21031	0.88534	1.4450	2	9.8263e−04
EHHO	0.03659	55.6394	0.76077	0.586184	0.240965	1.9684	1.4569	9.83606e−04
GA	0.0364	53.7185	0.7608	0.0001	0.0001	1.3355	1.481	3.6040e-01
WHHO	0.03673	55.4264	0.760781	0.228574	0.727182	1.451895	2	9.82487e−04

Generalised oppositional teaching learning-based optimisation (GOTLBO) has an error of (9.8742e−04), and (9.8293e−04) error for Improved JAYA optimisation algorithm (IJAYA), Performance-guided JAYA algorithm (PGJAYA)has an error value of (9.8263e−04), Enhanced Harris Hawk Optimization (EHHO) (9.83606e−04), Genetic algorithm (GA) (3.6040 e-01), Whippy Harris Hawks Optimization algorithm (WHHO) (9.82487e−04), According to these values in the table (10), it is clear that the suggested algorithm offers the most sufficient answer which is (**7.28000 e-04**).

As it is clear in this figure 15, the worst answer is related to the GA algorithm, and the answer obtained by the PSO algorithm has a lower value than the other answers.

IPSO	GOTLBO	PSO	IJAYA	PGJAYA	EHHO	GA	WHHO
7.280001e-04	9.8742e−04	9.8638e−04	9.8293e−04	9.8263e−04	9.83606e−04	3.6040 e-01	9.82487e−04

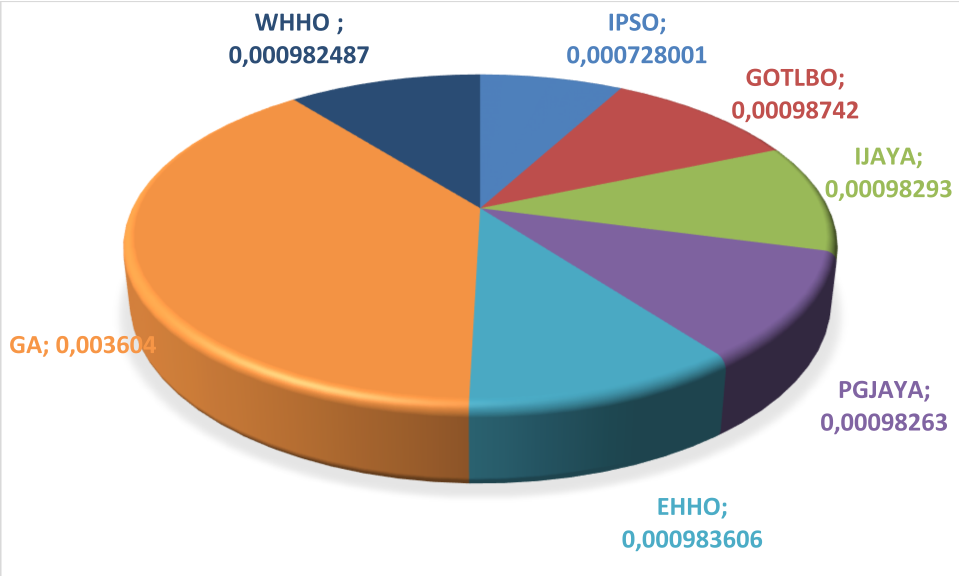

Figure 15. Values of (RMSE) for different algorithms in 2-diode model

As depicted in Figures 16 and 17, the outcomes of the suggested algorithm are juxtaposed with those of the practical test in the shape of power-voltage and current-voltage diagrams graphs.

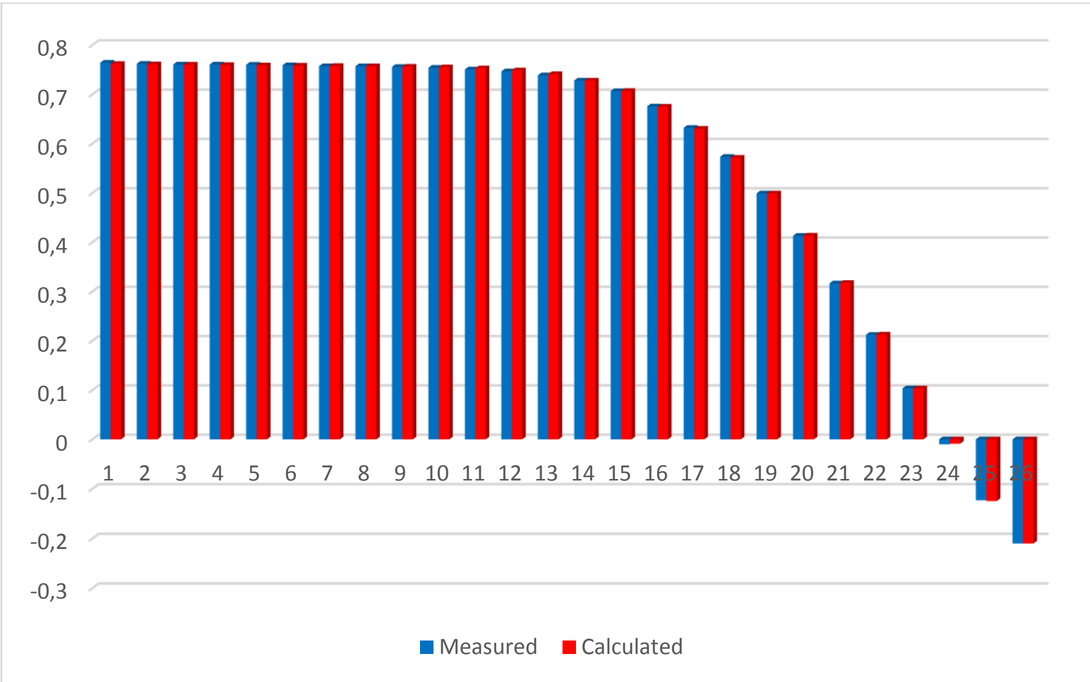

Figure 16. Comparison of the output Current from the practical test with the simulation in a two-diode model

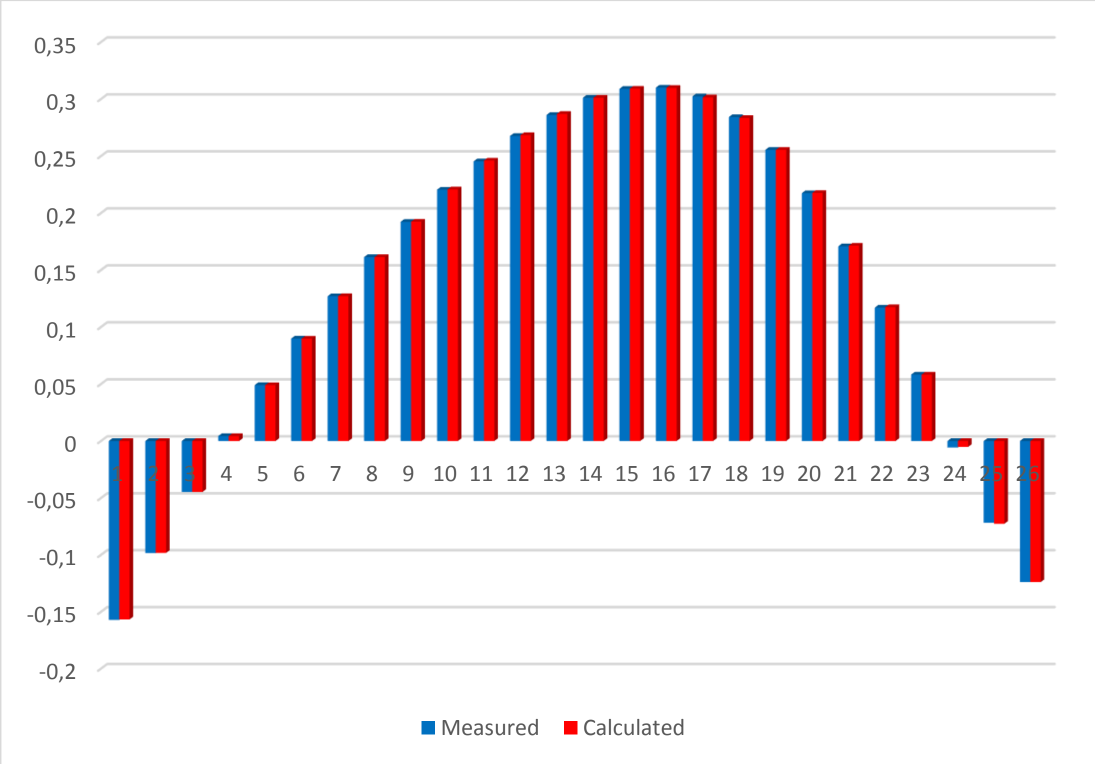

Figure 17. Comparison of solar cell output Power obtained from practical test and simulation in two diode model

4.4. Optimization results for the three-diode model

The algorithm has been implemented ten times for different numbers of PSOs. The results obtained from the simulation are summarised in Table 11.

Table 11. Comparing the results of ten times of running the PSO algorithm for the three-diode solar cell model

no.of particles	PSO=10	PSO=30	PSO=50	PSO=70	PSO=90	PSO=100
Iph	**0.760679942**	0.76067081	0.76070543	0.760636187	0.760630867	0.760609024
Isd1	**0.29732343**	0.1172962	0.35188447	0.18544709	0.1072768	0.12005112
Isd2	**0.25315449**	0.28067481	0.35327324	0.12346359	0.00115486	0.16124126
Isd3	**0.359165182**	0.185357913	0.10722626	0.158410673	0.244593469	0.576799389

Rsh	**67.58780816**	67.04708835	66.29484028	66.8388473	66.00964118	66.34271721
Rs	**0.035118202**	0.035236171	0.035175123	0.035243576	0.035354777	0.035446138
Ns1	**1.587032778**	1.600675505	1.610331082	1.615033137	1.601294317	1.607028341
Ns2	**1.612334891**	1.62439154	1.64670298	1.658731788	1.659161609	1.666934638
Ns3	**1.6154362**	1.60392549	1.60628455	1.6306997	1.61369572	1.60935072
RMSE	**6.966e-04**	6.966e-04	6.966e-04	6.966e-04	6.966e-04	6.966e-04

To confirm the accuracy of the IPSO optimization algorithm, the program has been executed ten times, and its results are given in Table 12. By comparing the response of these executions, it is noticeable that the changes in the objective function are very small. This proves that the proper performance of the algorithm was not random.

Table 12. Comparison of the outcomes of 10 times running the algorithm for the three-diode solar cell model

First 5 runs					
outcomes	Run 1	Run 2	Run 3	Run 4	Run 5
Iph	0.7608	0.7608	0.7605	0.7614	0.7603
Isd1	0.1995	0.1237	0.1489	0.3307	0.1855
Isd2	0.2591	0.1870	0.1326	0.0848	0.3380
Isd3	0.925667	0.1518088	0.234680758	0.3378643	0.3347597
Rsh	56.28508	55.0707	60.7648	48.1124	81.3038
Rs	0.038057745	0.03542337	0.035284299	0.035417978	0.036329615
n1	1.4422	1.4246	1.5716	1.7090	1.7264
n2	1.9967	1.6517	1.4325	1.3872	1.7208
N3	2	1.5804	1.6812	1.7119	1.7027
RMSE	0.00069663	0.00068758	0.00071209	0.00071958	0.00070875

Second 5 runs					
Results	Run 6	Run 7	Run 8	Run 9	Run 10
Iph	0.7608	0.7612	0.7608	0.7609	0.760679942
Isd1	0.3395	0.2999	0.3353	0.3448	0.29732343
Isd2	0.3119	0.2592	0.2520	0.3471	0.25315449
Isd3	0.925667	0.1695	0.3237	0.100	0.359165182
Rsh	56.1500	64.3129	59.1286	55.7429	67.58780816
Rs	0.038057745	0.03542337	0.035284299	0.035417978	0.035118202
n1	1.7264	1.6621	1.7043	1.7131	1.587032778
n2	1.7027	1.5485	1.4049	1.7514	1.612334891
n3	1.3862	1.5123	1.6827	1.73978	1.6154362
RMSE	0.00068758	0.00071209	0.00071958	0.00072112	0.00069663

According to Table 12, the implementation, which has the lowest amount of error at PSO=10 with the value of (6.966263e-04) is considered as the result of the algorithm, and we compare it with the answer of other algorithms in Table 13. It should be noted that the results of other algorithms are taken from reference (AlHajri et al., 2012).

Table 13. Comparing the results of different algorithms in the three-diode solar cell model

Parameter	I-PSO	GOTLBO	PSO	IJAYA	PGJAYA	EHHO	GA	WHHO
Iph(A)	**0.760718**	0.7607	0.7607	0.7608	0.7607	0.76078197	0.7605	0.76078248
Isd1(μA)	**0.746098**	0.2238	0.2259	0.2349	0.2144	0.22854289	0.3251	0.23910895
Isd2(μA)	**0.281989**	0.7583	0.7491	0.2297	0.8059	0.57999742	0.3608	0.43972073
Isd3(μA)	**0.0097088**	0.0184	0.0023	0.2297	0.1178	0.5861	0	0.8
Rs (Ω)	**0.035933**	0.0367	0.0367	0.0367	0.0368	0.03676206	0.0357	0.03672493
Rsh (Ω)	**63.390778**	55.4743	55.47571	55.2641	55.7500	55.77064030	58.6086	55.64995795
Ns1	**1.641042**	1.4501	1.4509	1.4541	1.4464	1.45029359	1.4843	1.45393749
Ns2	**1.606881**	2	2	1.8695	2	2	1.9975	2
Ns3	**1.654604**	2.3191	2.3156	2	2.2982	2.39655345	2.2099	2.40415974
RMSE	**6.966263 e-04**	9.8245e-04	9.8247e-04	9.8253e-04	9.8234e-04	9.81232e-04	1.0531e-03	9.80751e-04

According to Table 13, it is clear that the I-PSO algorithm has the best answer, followed by WHHO, EHHO, PGJAYA, GOTLBO, PSO, IJAYA, and GA. Where the GA has the maximum error value in the table. In Figure 18, the value of the objective function (RMSE) of different algorithms is compared with each other. As it is clear in this figure, the worst answer is related to the GA algorithm.

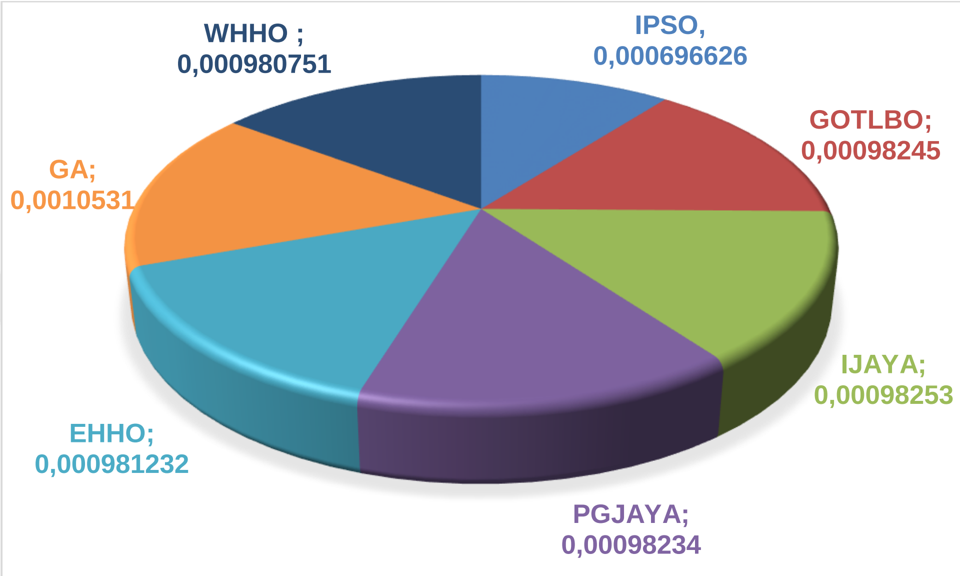

Figure 18. The value of (RMSE) of different algorithms in the three-diode model

It can be observed from the Figure that utilising the modified PSO optimisation method has yielded the most optimal outcome regarding the objective function of the RMSE, with a value of 6.966263 E-04 being the minimum.

In Figures 19 and 20, the outcomes of the proposed algorithm are compared with the outcomes of the practical test in the form of power-voltage and current-voltage diagrams.

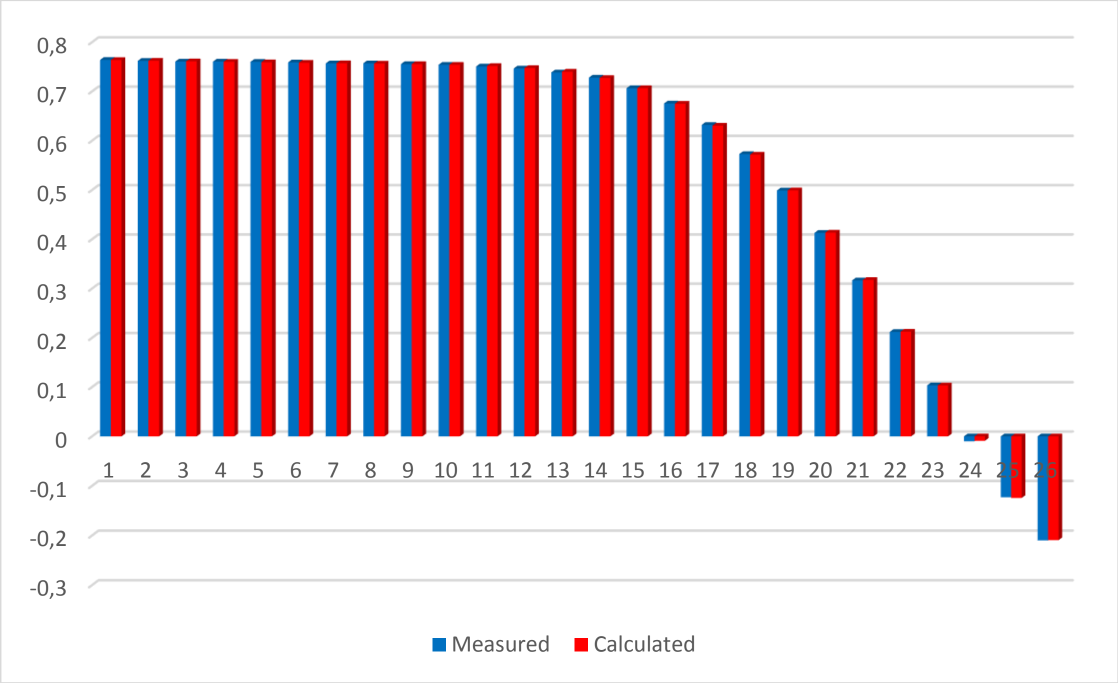

Figure 19. Comparison of the terminal current obtained from the practical test and simulation in the Three-diode model

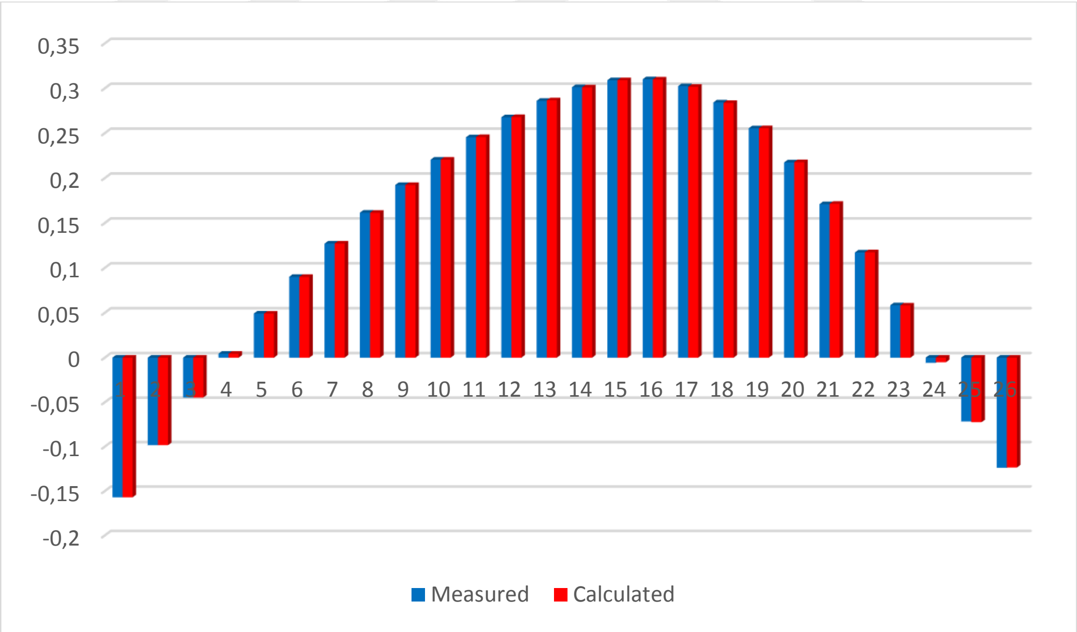

Figure 20. Comparison of solar cell output power obtained from practical test and simulation in Three diode model

The TDM exhibits a relatively more miner RMSE than the 1-DM and the 2-DM, which is easily observable. However, compared to the methods reported in the comparison tables, the 1-DM and 2-DM produce superior outcomes. Moreover, the optimisation of the proposed method has been executed for 10 implements for each population. The lowest value of the objective function has been captured and stated as the most favourable outcome for each trial.

CHAPTER FİVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

In this current thesis, the problem of parameter estimation has been investigated for Photovoltaic (PV) systems. the optimal design of one, two and three-diode solar cell models has been studied. For this reason, the improved PSO algorithm, which is a modified PSO algorithm, has been used. Modeling was done considering the objective function (RMSE).

According to the MATLAB environment simulation results, this proposed algorithm is extra accurate in locating the precise parameters of the solar cell than PSO, GOTLBO, IJAYA, PGAYA, EHHO, GA, WHHO and MLBSA. Taking into account the minor difference between the amount of the practical test and the output of the algorithm as a consequence of the error in recording the results of the practical test and the approximation of the utilised models. In other words, the RMSE value can be significantly decreased if the practical results are recorded more precisely, and a better model for the solar cell is developed.

Undoubtedly, The obtained results for the solar cell's parameters are trustworthy for modelling the solar cell. Regardless of the wide range of cases, there remains an opportunity to enhance present remedies through novel methodologies and algorithms. It is crucial to keep in mind that proposing an entirely new solar cell model, despite its potential to complicate calculations, may not be an effective strategy for reducing present error when compared to enhancing the precision of empirical test outcomes. Meanwhile, parameters of solar cells determined by the PSO algorithm can be utilised in applications other than MPP. Also, based on the outcomes derived from the models of one, two, and three-diode solar cells, it can be inferred that these models exhibit comparable results and possess nearly equivalent levels of precision.

The rationale beneath this can be related to the algorithm's exceptional precision in identifying the most suitable parameter value. The proposed study advocates for an optimization method that employs particle swarm optimization (PSO) to enhance the performance of the original PSO methodology. The proposed algorithm possesses certain amazing characteristics, including high resilience, global exploration, and convergence. To evaluate the efficacy of the proposed approach, the model parameters of PV cells have been found for the SDM, DDM, and TDM.

Our findings have been carefully evaluated against the established and proven methods outlined in the relevant literature. After conducting thorough tests, we discovered that the projected results closely aligned with the experimental data from the modules. This proves that the proposed algorithm is both effective and precise.

The key benefit of this thesis is the minimal error between the true value of the calculated current and the measured current. In addition, this approach employed a small sample size of agents to determine the optimal value for each diode module's parameter. The suggested PSO approach has successfully located the global minimum and avoided getting stuck in the local minimum to get the aforementioned parameters.

5.2. Future works

With the present thesis usage, the Improved Particle swarm optimization algorithm, optimal modelling of 1-diode, 2-diode, and 3-diode solar cell models were investigated; future studies might focus on the following areas:

1- It is achievable to utilise alternative solar cell models and to compare the findings obtained with the real results and the results achieved in this study.

2- A more precise model of a solar cell may also be obtained by using modern implemented methods.

3- There is always scope for improving the proposed algorithm to enhance local search capabilities and achieve optimal solutions. Combining the proposed algorithm with other optimisation algorithms in a hybrid strategy can lead to improved performance. A hybrid approach might be a valuable and effective means of optimising the suggested algorithm.

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RESUME

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Education

Degree	Education Unit	Graduation Date
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Work Experience

Year	Place	Title

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Publications

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