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Improving the efficiency of solar panel systems using Newton-Raphson

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Dedication

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✍Fatima Zahra

Abstract

Photovoltaic (PV) energy has become one of the most important renewable energy sources due to its environmental benefits, abundance, and growing technological development. However, the accurate modeling and parameter identification of photovoltaic panels remain challenging because of the nonlinear characteristics of PV systems and their dependence on environmental conditions such as temperature and solar irradiance. In this context, optimization algorithms have been widely employed to improve the accuracy of photovoltaic parameter estimation. This dissertation presents the application of the Newton–Raphson-Based Optimizer (NRBO) for the optimization of photovoltaic panel parameters. The proposed approach combines the mathematical efficiency of the Newton–Raphson method with stochastic optimization mechanisms in order to achieve an effective balance between exploration and exploitation of the search space. The study focuses on identifying the optimal parameters of the photovoltaic model by minimizing the error between experimental and estimated electrical characteristics. The NRBO algorithm was implemented using MATLAB and applied to the single-diode photovoltaic model. Several simulation results were obtained and analyzed through convergence curves, current–voltage (I–V) characteristics, and power–voltage (P–V) characteristics. The obtained results demonstrated a rapid convergence speed and a high accuracy in reproducing the real behavior of the photovoltaic module. Furthermore, the close agreement between experimental and estimated curves confirmed the effectiveness and robustness of the proposed optimization technique. The results obtained in this work show that the NRBO algorithm is a promising and efficient optimization tool for photovoltaic parameter identification and renewable energy applications.

Keywords: Photovoltaic System (PV), Newton–Raphson-Based Optimizer (NRBO), Parameter Identification, I–V Characteristics, P–V Characteristics, Single-Diode Model

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الملخص

تُعد الطاقة الشمسية الكهروضوئية من أهم مصادر الطاقة المتجددة نظراً لما تتميز به من وفرة ونظافة وإمكانية استغلالها في العديد من التطبيقات الصناعية والمنزلية. غير أن النمذجة الدقيقة للألواح الشمسية واستخراج معاملاتها الكهربائية يمثلان تحدياً كبيراً بسبب الطبيعة غير الخطية للأنظمة الكهروضوئية وتأثرها بالعوامل المناخية المختلفة مثل درجة الحرارة والإشعاع الشمسي. لذلك، أصبح الاعتماد على خوارزميات التحسين الحديثة أمراً ضرورياً لتحسين دقة نماذج الأنظمة الكهروضوئية. تهدف هذه المذكرة إلى دراسة وتطبيق خوارزمية التحسين المعتمدة على نيوتن–رافسون (Newton–Raphson-Based Optimizer: NRBO) من أجل تحسين معاملات اللوح الشمسي. تعتمد هذه الخوارزمية على الجمع بين الكفاءة الرياضية لطريقة نيوتن–رافسون وتقنيات البحث العشوائي الذكي لتحقيق توازن فعال بين الاستكشاف والاستغلال داخل فضاء البحث. وقد تم توظيف هذه الخوارزمية لتحديد المعاملات المثلى للنموذج الكهروضوئي من خلال تقليل الخطأ بين القيم التجريبية والقيم المقدرة. تمت برمجة خوارزمية NRBO باستخدام برنامج MATLAB وتطبيقها على نموذج اللوح الشمسي أحادي الديود. كما تم تحليل النتائج المتحصل عليها من خلال دراسة منحنيات التقارب وخصائص التيار–الجهد (I–V) والقدرة–الجهد (P–V). وقد أظهرت النتائج سرعة تقارب عالية ودقة كبيرة في تمثيل السلوك الحقيقي للمنظومة الكهروضوئية، إضافة إلى تطابق جيد بين النتائج التجريبية والمحاكاة. تؤكد النتائج المتحصل عليها فعالية خوارزمية NRBO وقدرتها على تحسين معاملات الأنظمة الكهروضوئية بكفاءة عالية، مما يجعلها أداة واعدة في مجال تحسين أداء أنظمة الطاقة المتجددة.

الكلمات المفتاحية: النظام الكهروضوئي(PV) ، خوارزمية التحسين المعتمدة على نيوتن–رافسون (NRBO)، تحديد المعاملات، خصائص التيار–الجهد(I–V) ، خصائص القدرة–الجهد(P–V) ، نموذج الديود الأحادي.

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Summary

General Introduction

General Introduction

With the continuous increase in global energy demand and the environmental challenges caused by the excessive use of fossil fuels, renewable energy sources have become one of the most promising solutions for achieving sustainable development and reducing greenhouse gas emissions. Among the various renewable energy sources, photovoltaic (PV) solar energy has attracted considerable attention due to its abundance, cleanliness, and ease of integration into industrial and residential applications.

The efficiency and performance of photovoltaic systems strongly depend on the accurate modeling of solar panels and the precise extraction of their electrical parameters, such as the photocurrent, diode saturation current, and internal resistances. Parameter identification remains one of the major challenges in photovoltaic system modeling because of the nonlinear nature of PV characteristics and their dependence on environmental conditions such as solar irradiance and temperature.

In recent years, optimization techniques and artificial intelligence approaches have been widely employed to improve photovoltaic parameter estimation. These advanced optimization methods have demonstrated remarkable capabilities in solving nonlinear and complex engineering problems. Among these techniques, the Newton–Raphson-Based Optimizer (NRBO) has emerged as an efficient and powerful optimization algorithm that combines the mathematical principles of the Newton–Raphson method with stochastic search mechanisms to achieve a balanced exploration and exploitation of the search space.

The main objective of this dissertation is to investigate and apply the NRBO algorithm for the optimization of photovoltaic panel parameters in order to develop an accurate PV model capable of reproducing the real electrical behavior of the photovoltaic system. The study also aims to evaluate the effectiveness of the proposed optimization technique through the analysis of convergence behavior, current–voltage (I–V) characteristics, and power–voltage (P–V) characteristics, as well as by comparing the estimated results with experimental data.

In this work, the NRBO algorithm is implemented using MATLAB software and applied to the single-diode photovoltaic model in order to identify the optimal PV parameters while minimizing the error between the measured and estimated values. The obtained results are analyzed through several graphical representations and numerical indicators that demonstrate the efficiency, stability, and accuracy of the optimization process.

This dissertation is organized into three main chapters.

The first chapter presents the theoretical background of photovoltaic energy systems. It introduces the operating principles of solar cells, different types of photovoltaic panels, and the mathematical models commonly used to represent photovoltaic systems.

The second chapter is devoted to the study of the Newton–Raphson-Based Optimizer (NRBO). It describes the mathematical foundations of the algorithm, its operating principles, the associated flowchart, and the different optimization stages including initialization, the Newton–Raphson Search Rule (NRSR), and the Trap Avoidance Operator (TAO).

The third chapter focuses on the practical implementation of the NRBO algorithm for photovoltaic parameter optimization using MATLAB. It also presents and discusses the obtained simulation results through convergence analysis and I–V and P–V characteristic curves, highlighting the accuracy and effectiveness of the proposed optimization approach.

Finally, the dissertation concludes with a general conclusion summarizing the main findings of the study and proposing several future research perspectives related to intelligent optimization techniques and their applications in renewable energy systems.

Chapter I

Introduction and Fundamentals

1.1 Introduction

Optimization plays a crucial role in engineering, science, and industrial applications. It consists of determining the best possible solution among a set of feasible alternatives in order to minimize or maximize a given objective function while satisfying certain constraints. In many real-world systems, optimization problems are highly complex due to nonlinear relationships, large search spaces, and multiple interacting variables [4].

Traditional optimization techniques, although mathematically rigorous, may become inefficient when applied to large-scale or highly nonlinear problems. To address these challenges, metaheuristic algorithms have been developed. These algorithms are flexible optimization approaches designed to explore the search space efficiently and provide near-optimal solutions within reasonable computational time [6].

Metaheuristic methods are often inspired by natural phenomena such as biological evolution, swarm intelligence, or physical processes. These techniques have been widely used in different fields including engineering design, machine learning, scheduling, and renewable energy systems [7].

Recently, Ravichandran Sowmya, Manharan Premkumar, and Pradeep Jangir proposed a new optimization algorithm known as the **Newton-Raphson Based Optimizer (NRBO)** in 2023. This algorithm combines the classical Newton–Raphson numerical method with modern optimization strategies such as the Newton-Raphson search rule and a trap avoidance operator to improve convergence and avoid local optima [1].

Therefore, this chapter presents the fundamental concepts of optimization, different types of optimization problems, and various optimization techniques, with particular emphasis on metaheuristic algorithms.

I.2 Definition of Optimization Problem

An optimization problem aims to determine the best values of decision variables that optimize an objective function while satisfying a set of constraints. The computational difficulty of an optimization problem largely depends on the mathematical properties of the objective function and the nature of the constraints involved [4].

Optimization has long been present in human activities. Individuals naturally attempt to obtain the best outcomes while operating under limited resources and uncertain conditions.

Over time, various optimization strategies have evolved based on observations of natural systems and accumulated practical experience [7].

In engineering and scientific applications, optimization problems can involve either a single objective or multiple objectives. **Single-objective optimization** focuses on optimizing a single performance criterion, whereas **multi-objective optimization** aims to optimize several conflicting objectives simultaneously [2].

In the context of multi-objective optimization, the concept of **Pareto optimality** is often used to define optimal solutions. A solution is considered Pareto optimal if no other solution can improve one objective without degrading at least one other objective [3].

I.3 Mathematical Formulation of Optimization Problems

An optimization problem can generally be formulated mathematically as follows:

Find $X=\begin{Bmatrix} x1 \\ x2 \\ . \\ . \\ . \\ xp \end{Bmatrix}$ to Minimize or maximize $f(x)$

(I.1)

Subject to:

$$g_i(x) \leq 0, i = 1,2,\ldots,m \tag{I.2}$$

$$h_j(x) = 0, j = 1,2,\ldots,p \tag{I.3}$$

Where $x$represents the vector of decision variables, $f(x)$is the objective function, $g_i(x)$are inequality constraints, and $h_j(x)$are equality constraints [4].

When constraints are present, the problem is referred to as a **constrained optimization problem**. Otherwise, it is called an **unconstrained optimization problem**.

In many optimization landscapes, the objective function may contain several local maxima and minima. The main objective of optimization algorithms is therefore to locate the global optimum, which represents the best solution in the entire search space [5].

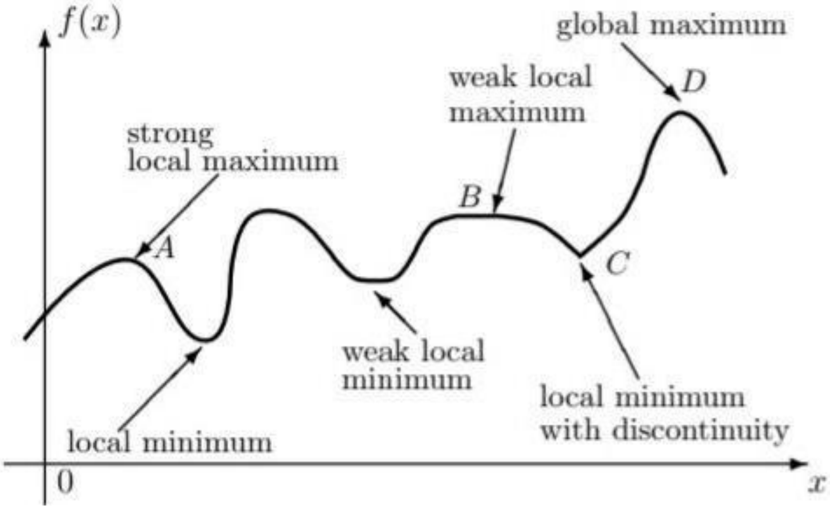

Figure I.1: *Strong and weak maxima and minima*

The condition ($f'(x^*) = 0$) does not hold in this case. Therefore, we will not examine this type of minimum or maximum in depth. For our current discussion, we will assume that both $f(x)$ and ($f'(x)$) are always continuous, or equivalently, that $f(x)$ is twice continuously differentiable everywhere.

I.4 Classification of Optimization Problems

Optimization problems can be classified according to several criteria depending on their mathematical structure and practical characteristics [4].

I.4.1 Based on Constraints

Optimization problems can be classified as **constrained** or **unconstrained**, depending on whether restrictions are imposed on the decision variables [4].

I.4.2 Based on Design Variables

Optimization problems can also be categorized according to the nature of their variables.

Parameter optimization problems involve determining optimal values of a finite set of parameters.

Functional optimization problems, on the other hand, involve determining optimal functions rather than discrete parameters [5].

I.4.3 Based on Mathematical Formulation

According to the mathematical form of the objective function and constraints, optimization problems may be categorized into several classes such as linear programming, nonlinear programming, quadratic programming, and geometric programming [4].

I.4.4 Based on Variable Nature

Optimization problems may also be classified as **deterministic** or **stochastic**.

In deterministic problems, all parameters are known with certainty, whereas stochastic optimization problems involve variables that are subject to randomness or uncertainty [7].

I.4.5 Based on Number of Objectives

Depending on the number of objective functions involved, optimization problems can be divided into **single-objective optimization** and **multi-objective optimization** problems [2].

I.5 Optimization Techniques

Optimization techniques are generally divided into two major categories: *exact methods* and *approximate methods* [5].

I.5.1 Exact Methods

Exact methods aim to determine the true global optimum of an optimization problem using rigorous mathematical procedures. Examples include linear programming, dynamic programming, and integer programming [4].

Although these techniques guarantee optimal solutions, they may become computationally expensive when applied to large-scale or highly nonlinear problems [5].

I.5.2 Approximate Methods

Approximate methods, also known as heuristic or metaheuristic methods, are commonly used when the complexity of the problem makes exhaustive search impractical. These approaches provide good approximate solutions within reasonable computational time [6].

Metaheuristic techniques rely on intelligent search mechanisms, stochastic processes, and adaptive strategies to efficiently explore the search space [7].

I.6 Metaheuristic Algorithms

Metaheuristic algorithms are powerful tools for solving complex optimization problems. They have been widely applied in engineering and scientific fields due to their ability to efficiently explore large search spaces and avoid premature convergence [6].

Most metaheuristic algorithms share several important characteristics. First, they usually employ stochastic search mechanisms to explore the solution space effectively. Second, they do not require gradient information, which makes them suitable for nonlinear and non-differentiable problems. Finally, many of these algorithms are inspired by natural phenomena such as biological evolution, swarm behavior, or physical processes [7].

Despite their advantages, metaheuristic algorithms may require careful parameter tuning and do not always guarantee finding the exact global optimum [6].

I.7 Common Metaheuristic Algorithms

Several metaheuristic algorithms have been proposed in the literature, figure 1.2 shows metaheuristic algorithms.

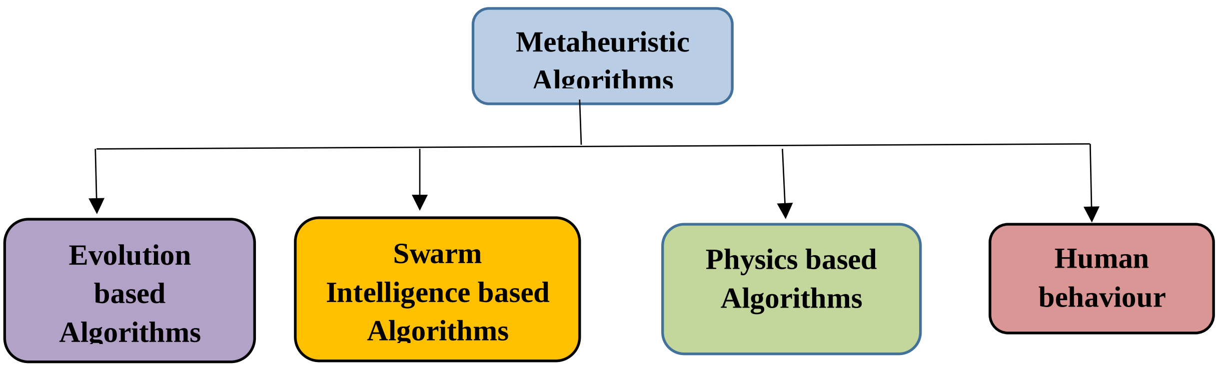

Figure I.2: *Metaheuristic Algorithm classification*

The **Genetic Algorithm (GA)** is inspired by the principles of natural evolution and genetics. It uses operators such as selection, crossover, and mutation to evolve a population of candidate solutions toward better solutions [10].

The **Particle Swarm Optimization (PSO)** algorithm is based on the collective behavior of bird flocks and fish schools, where particles move through the search space while sharing information about the best solutions found [8].

The **Simulated Annealing (SA)** algorithm is inspired by the physical annealing process used in metallurgy, where temperature is gradually reduced to reach a stable state [6].

The **Ant Colony Optimization (ACO)** algorithm mimics the foraging behavior of ants, which communicate using pheromone trails to identify the shortest path between food sources and their colony [9].

I.8 General application of metaheuristics

Metaheuristics have been widely applied to various domains and problem types due to their flexibility and ability to find near-optimal solutions. Some applications of metaheuristics include:

- ✓ **Combinatorial Optimization:** Metaheuristic algorithms are extensively used for solving combinatorial optimization problems such as the Traveling Salesman Problem, Vehicle Routing Problem, Knapsack Problem, and Graph Coloring Problem.
- ✓ **Scheduling and Timetabling*:*** Metaheuristics are employed to optimize scheduling and timetabling problems, including employee scheduling, project scheduling, course timetabling, and production planning.
- ✓ **Machine Learning and Data Mining*:*** Metaheuristic algorithms are utilized in feature selection, parameter tuning, and model optimization for machine learning and data mining tasks.
- ✓ **Image and Signal Processing:** Metaheuristics find applications in image and signal processing tasks such as image reconstruction, image segmentation, denoising, and optimization of filter design.
- ✓ **Engineering Design and Optimization:** Metaheuristic techniques are used for engineering design optimization problems, including structural optimization, parameter estimation, and optimal control.
- ✓ **Portfolio Optimization:** Metaheuristics are employed to optimize investment portfolios by finding the best allocation of assets to maximize returns while minimizing risk.
- ✓ **Energy Optimization:** Metaheuristics assist in optimizing energy systems and resources, such as power generation and distribution, renewable energy integration, and energy-efficient routing in wireless sensor networks.

- ✓ **Bioinformatics:** Metaheuristics are applied to bioinformatics problems, including sequence alignment, protein folding, gene expression analysis, and DNA motif discovery.

I.9 Application of Optimization in Photovoltaic Systems

Photovoltaic (PV) systems represent one of the most promising renewable energy technologies due to their ability to convert solar radiation directly into electrical energy without producing greenhouse gas emissions [13].

However, the performance of PV systems is strongly influenced by environmental conditions such as solar irradiance, temperature, and partial shading. As a result, optimization techniques are widely used to improve the efficiency and performance of PV systems [14,15].

One of the most important applications of optimization in photovoltaic systems is **Maximum Power Point Tracking (MPPT)**. The electrical characteristics of a PV module are nonlinear, and the operating point corresponding to the maximum output power varies depending on environmental conditions. Optimization algorithms are therefore employed to continuously locate the **maximum power point (MPP)** and maximize the energy harvested from the PV system [14].

Metaheuristic algorithms such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization have been successfully applied to solve MPPT problems and improve the efficiency of PV systems under varying environmental conditions [6].

In addition to MPPT, optimization techniques are also used for PV system sizing, optimal placement of photovoltaic panels, parameter estimation of PV models, and control of power electronic converters used in solar energy systems [13].

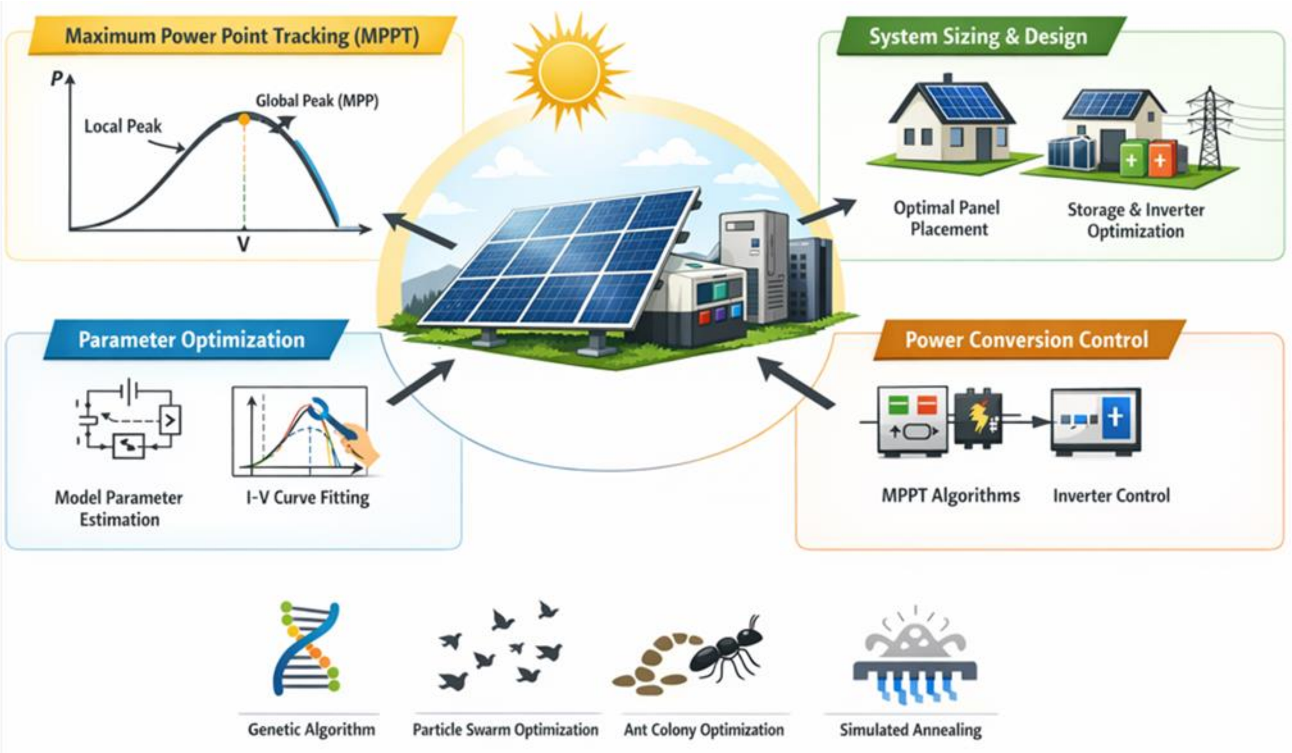

Figure I.3: *Principal parts of PV optimization*

I.10 Conclusion

This chapter presented the fundamental concepts related to optimization and the main techniques used to solve optimization problems. First, the general definition and mathematical formulation of optimization problems were introduced, highlighting the role of objective functions, decision variables, and constraints in determining optimal solutions. Different classifications of optimization problems were also discussed based on criteria such as the nature of variables, the presence of constraints, and the number of objective functions.

Furthermore, the chapter reviewed the main categories of optimization methods, including exact methods and approximate techniques. Particular attention was given to metaheuristic algorithms, which have proven to be powerful tools for solving complex and nonlinear optimization problems due to their flexibility and efficiency in exploring large search spaces.

Several well-known metaheuristic algorithms such as Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, and Ant Colony Optimization were briefly presented along with their main characteristics and applications. Finally, the importance of optimization techniques in renewable energy systems, particularly photovoltaic systems, was highlighted, especially for applications such as Maximum Power Point Tracking and PV system design.

The concepts introduced in this chapter provide the theoretical foundation necessary for the following chapters, where optimization algorithms will be applied to improve the performance and efficiency of photovoltaic energy systems.

Chapter II

Newton-Raphson-Based Optimization Method

II. 1 Introduction:

The Newton-Raphson-Based Optimizer (NRBO) is a state-of-the-art metaheuristic optimization algorithm introduced in 2023. It represents a significant advancement in the field of computational intelligence by bridging the gap between classical numerical analysis and modern population-based search strategies. While traditional optimization methods often struggle with balancing the exploration of unknown regions and the exploitation of known local minima, NRBO leverages the mathematical rigor of the Newton-Raphson Method (NRM) to navigate complex search landscapes effectively [1].

The core philosophy of NRBO is rooted in the Taylor Series expansion, which provides a framework for approximating the behavior of a function based on its derivatives. In its original form, the Newton-Raphson method is a deterministic root-finding algorithm that uses first and second-order derivatives to move rapidly toward a solution. NRBO transforms this logic into a stochastic process suitable for global optimization. Instead of relying on analytical derivatives—which are often unavailable in real-world engineering problems—NRBO utilizes the positions of agents within a population to estimate the trajectory toward the optimum. This is primarily achieved through the Newton-Raphson Search Rule (NRSR), which calculates "stochastic jumps" by comparing the best and worst-performing agents in the current iteration [2,3].

To enhance its robustness, NRBO incorporates a Trap Avoidance Operator (TAO). This mechanism is crucial for maintaining population diversity and preventing the "entrapment" of agents in local optima, a common failure point for many gradient-based methods. By combining these adaptive search rules with a dynamic step-size control, the algorithm achieves a high degree of convergence speed without sacrificing the thoroughness of its global search [4].

NRBO has demonstrated exceptional performance across various benchmarks, including constrained and unconstrained single-objective problems. By modernizing a classic mathematical principle, NRBO provides a powerful, efficient, and reliable tool for solving the intricate optimization challenges of the contemporary era.

II. 2 Advanced Computational Optimization and the Mathematical Framework:

The progression of modern engineering and telecommunications is increasingly defined by the ability to solve complex, non-linear optimization problems within highly dynamic environments. At the intersection of numerical analysis and computational intelligence lies the development of metaheuristic algorithms designed to navigate search spaces that are often too intricate for classical exact methods. Among these innovations, the Newton-Raphson-Based Optimizer (NRBO), introduced in 2024 by Ravichandran Sowmya, Manoharan Premkumar, and Pradeep Jangir, stands as a sophisticated population-based approach that synthesizes the deterministic precision of second-order numerical techniques with the stochastic robustness of metaheuristic search [5-7].

II. 3 Theoretical Context of Global Optimization and Metaheuristic Evolution:

The discipline of optimization involves the systematic identification of the best possible values for a set of decision variables, governed by specific constraints, to either maximize or minimize an objective function. The tractability of such problems is fundamentally determined by the structural properties of the objective function and its constraints, such as linearity, differentiability, and continuity. Traditional exact techniques, including linear programming and integer programming, provide guarantees for reaching the true global optimum but often encounter exponential computational growth when applied to large-scale, high-dimensional, or non-convex problems [8].

As real-world challenges in engineering, economics, and telecommunications have grown in complexity, the limitations of exact methods led to the emergence of approximate techniques, commonly categorized as heuristics and metaheuristics. Metaheuristics are flexible, higher-level frameworks that guide a search process to explore vast solution spaces efficiently. These algorithms are frequently inspired by biological systems, physical processes, or mathematical rules, utilizing stochasticity to avoid the local optima entrapment that often plagues gradient-descent methods.

Table II.1: *Classification and Comparative Characteristics of Optimization Techniques*

Optimization Technique Category	Primary Characteristics	Common Examples
Exact Techniques	Guarantee global optimum; high precision; mathematically rigorous.	Linear Programming (LP), Integer Programming, Branch and Bound.
Approximate Techniques	Provide near-optimal solutions; computationally efficient for large scales.	Heuristics, Local Search, Tabu Search.
Metaheuristics	Guided stochastic search; nature-inspired; population-based.	Genetic Algorithms (GA), Particle Swarm Optimization (PSO), NRBO.

The evolution of these techniques has moved toward hybridization, where the local refinement capabilities of mathematical methods are integrated with the global exploration features of population-based algorithms. NRBO represents the pinnacle of this synthesis, leveraging the Newton-Raphson Method's second-order curvature information to accelerate convergence while maintaining a population-based diversity to handle multimodal landscapes [9].

II.4 Mathematical Reformulation of the Newton-Raphson-Based Optimizer

The Newton-Raphson-Based Optimizer is predicated upon the principles of the Newton-Raphson Method (NRM), a classical numerical root-finding algorithm. By extending the NRM logic into a population-based search strategy, NRBO utilizes the first and second-order derivatives of a function to define a search trajectory that is both purposeful and resilient against premature convergence [10,11].

II.5 Classical Inspiration and Taylor Series Derivation

The algorithmic inspiration for NRBO is the Taylor Series expansion, which provides a polynomial approximation of a function in the neighborhood of a point. For a twice-continuously differentiable function f(x), the Taylor Series expansion about a point x_0 with an offset ε is represented as [12-15]:

$$f(x_0+\epsilon)=f(x_0)+f'(x_0)e+\frac{f''(x_0)\,\epsilon^2}{2!}+\frac{f'''(x_0)\,\epsilon^3}{3!}+\cdots \quad (\mathrm{E}_q 1.5)[\mathrm{II},1]$$

In the search for a root, where f(x + ε) = 0, we truncate the series to preserve only the second-order terms, resulting in a quadratic approximation of the local functional landscape:

$$f(x_0+\epsilon) \approx f(x_0)+f'(x_0)\epsilon+\frac{f''(x_0)\epsilon^2}{2} \text{ (Eq I.6)}[\mathrm{II},2]$$

Solving this approximation for the offset ϵ, which we denote as ε_0, provides the refinement step necessary to move toward the optimum:

$$\epsilon_0=-\frac{f'(x_0)}{f''(x_0)} \left(\mathrm{B}_q 1.7\right)[\mathrm{II},3]$$

The iterative nature of the Newton-Raphson method allows for successive refinements of the solution estimate, defined as:

$$\epsilon_n=-\frac{f'(x_n)}{f''(x_n)} \text{ (Eq) }[\mathrm{II},4]$$

This leads to the fundamental update equation that governs the search trajectory in the classical NRM and serves as the core logic for the NRBO's search rules:

$$x_{n+1}=x_n-\frac{f'(x_n)}{f''(x_n)}, n=1,2,3,\ldots \text{ (Eq)}[\mathrm{II},5]$$

While the classical method is highly efficient, it requires the existence and calculation of the first and second derivatives, and it can be unstable if the initial guess is far from the optimum. NRBO overcomes these challenges by utilizing a population of agents and finite-difference approximations.

II. 6 Initialization and Population Representation

The NRBO algorithm begins its search for global optima by generating a population of candidate solutions within the boundary constraints of the decision space. For an optimization problem with *dim* dimensions, the lower and upper bounds are defined as [12-15]:

$$tb \leq x_j \leq ub, j=1,2,\ldots,\dim \text{ (Eq)}[\mathrm{II},6]$$

The initial population of N_p individuals is generated randomly, ensuring that the initial search covers a significant portion of the feasible region.

$$x_j^n=lb+\mathrm{rand}\times(ub-lb), n=1,2,\ldots,N, \text{ and } j=1,2,\ldots,\dim \text{ (Eq)}[\mathrm{II},7]$$

This population is represented as a matrix where each row is a solution vector and each column represents a specific dimension of the optimization problem:

$$[X_n] = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_{\mathrm{dm}}^1 \\ x_1^2 & x_2^2 & \dots & x_{\mathrm{dim}}^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^{Np} & x_2^{Np} & \dots & x_{dm}^{Np} \end{bmatrix} \quad (\text{Eq})[\text{II}, 8]$$

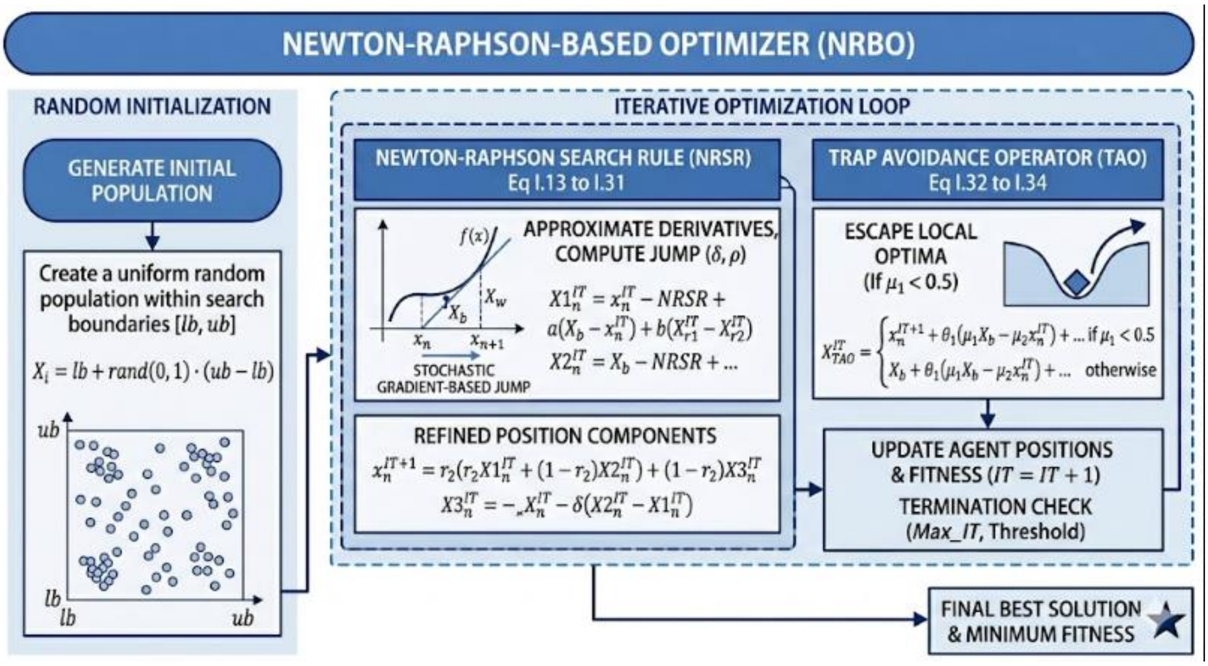

Figure II.1: *NRBO steps.*

The efficacy of this initialization is critical for providing the diversity needed to explore complex, multimodal landscapes where the global optimum may be hidden among many local minima.

II. 7 Newton-Raphson Search Rule (NRSR)

The central component of the NRBO's search mechanism is the Newton-Raphson Search Rule (NRSR), which simulates the derivative-based updates of the NRM using finite difference approximations derived from the function values of population members. To derive these approximations, we consider the function values at points displaced by a small distance Δx from the current position [12-15]:

$$f(x + \Delta x) = f(x) + f'(x_0)\Delta x + \frac{1}{2!}f''(x_0)\Delta x^2 + \frac{1}{3!}f'''(x_0)\Delta x^3 + \cdots \quad (\text{Eq})[\text{II}, 9]$$

$$f(x - \Delta x) = f(x) - f'(x_0)\Delta x + \frac{1}{2!}f''(x_0)\Delta x^2 - \frac{1}{3!}f'''(x_0)\Delta x^3 + \cdots \quad (\text{Eq})[\text{II}, 10]$$

By performing simple arithmetic operations on these expansions, we can approximate the first and second derivatives without the need for symbolic differentiation:

$$f'(x) = \frac{f(x+\Delta x) - f(x-\Delta x)}{2\Delta x} \Big) \text{(Eq)[II, 11]}$$

$$f''(x) = \frac{f(x+\Delta x) + f(x-\Delta x) - 2 \times f(x)}{\Delta x^2} \text{ (Eq)[II, 12]}$$

Substituting these finite difference expressions into the original Newton-Raphson update formula results in the discrete update rule:

$$x_{n+1} = x_n - \frac{\big(f(x_n+\Delta x) - f(x_n-\Delta x)\big) \times \Delta x}{2 \times \big(f(x_n+\Delta x) + f(x_n-\Delta x) - 2 \times f(x_n)\big)} \text{ (Eq)[II, 13]}$$

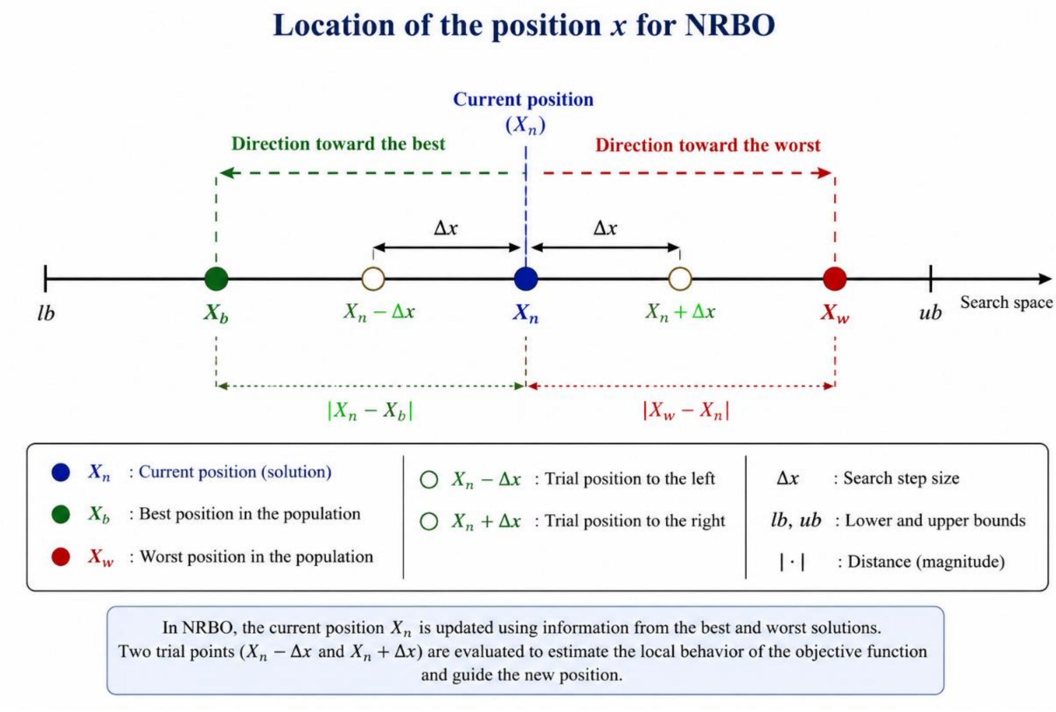

Figure II.2: *Location of the position x*

In the metaheuristic implementation of NRBO, the neighbors x+ Δx and x- Δx are replaced with vectors from the population. Specifically, for a minimization problem, a point with a worse fitness value X_ω replaces the forward neighbor, and a point with a better fitness value X_b replaces the backward neighbor, facilitating a search toward lower values of the objective function.

The NRSR is thus expressed as:

$$NRSR = \text{randn} \times \frac{(X_w - X_s) \times \Delta z}{2 \times (X_w + X_s - 2 \times x_n)} \text{ (Eq)[II, 14]}$$

Here, *randn* represents a random number drawn from a normal distribution with a mean of 0 and a variance of 1, ensuring that the search direction is probabilistic yet guided by the local "curvature" estimated from the agents X_ω and X_b.

II. 8 Dynamic Scaling and Adaptive Search Coefficients

A fundamental challenge in metaheuristic design is managing the transition from broad exploration in the early stages of search to fine-grained exploitation in the later stages. NRBO addresses this through an adaptive coefficient δ that scales the update step [15].

$$\delta = \left(1 - \left(\frac{2 \times IT}{\text{Max\_IT}}\right)\right)^5 \text{ (Eq)[II, 15]}$$

As the current iteration (IT) approaches the maximum iteration limit (Max_IT), the value of δ decreases, effectively reducing the step size and allowing the population to settle into a global optimum. The parameter Δx is also dynamically scaled based on the distance to the best solution identified thus far (X_b):

$$\Delta x = \text{rand}(1, \text{dim}) \times |X_s - X_n^{rT}| \text{ (Eq)[II, 16]}$$

The basic update rule for the vector position is then:

$$x_{n+1} = x_n - NRSR \text{ (Eq)[II, 17]}$$

Population-Based Guidance and Vector Refinement To further enhance the search capability and prevent stagnation, NRBO utilizes an additional guidance parameter ρ, which pulls the population members toward the optimal direction by leveraging the differences between the current best individual and randomly selected agents x_{r1} and x_{r2} from the population:

$$\rho = a \times \left(X_b - X_p^{JT}\right) + b \times \left(X_{p1}^{JT} - X_{r2}^{JT}\right) \text{(Eq)[II, 18]}$$

This guidance parameter is integrated into the update rule to produce the refined vector $X1_n^{IT}$, combining the finite-difference curvature approximation with a global search bias:

$$X1_n^{JT} = x_n^{JT} - \left(\text{rand } \times \frac{(X_\text{w} - X_\text{b}) \times \Delta x}{2 \times (X_\text{w} + X_\text{b} - 2 \times x_\text{n})}\right) + (a \times (X_\text{b} - X_n^{HT}) +$$

$$b \times \left(X_{r1}^{\Pi T} - X_{r2}^{JT}\right)\right) \text{ (Eq)[II, 19]}$$

The search rule is iteratively refined through a secondary process (Eq I.24 - I.31) that updates the neighborhood positions y_ω and y_b using the mean of the current and recently updated positions.

$$NRSR = \text{randn} \times \frac{(y_w - y_b) \times \Delta x}{2 \times (y_w + y_b - 2 \times x_n)} \text{ (Eq)[II, 20]}$$

$$y_w = r_1 \times (\text{Mean}(Z_{n+1} + x_n) + r_1 \times \Delta x) \text{ (Eq)[II, 21]}$$

$$y_b = r_1 \times (\text{Mean}(Z_{n+1} + x_n) - r_1 \times \Delta x) \text{ (Eq)[II, 22]}$$

$$Z_{n+1} = x_n - \text{randn} \times \frac{(X_w - X_b) \times \Delta x}{2 \times (X_w + X_b - 2 \times x_n)} \text{ (Eq)[II, 23]}$$

The final position update x_n^{IT+1} computed through a recursive process involving intermediate vectors $X2_n^{IT}$ and 3_n^{IT} :

$$X2_n^{IT} = x_b - \left(\text{randn} \times \frac{(y_w - y_b) \times \Delta x}{2 \times (y_w + y_b - 2 \times x_n)}\right) + \left(a \times (X_b - X_n^{IT}) + b \times (X_{r1}^{IT} - X_{r2}^{IT})\right) \text{ (Eq)[II, 24]}$$

$$x_n^{IT+1} = r_2 \times (r_2 \times X1_n^{IT} + (1 - r_2) \times X2_n^{IT}) + (1 - r_2) \times X3_n^{IT} \text{ (Eq)[II, 25]}$$

$$X3_n^{IT} = X_n^{IT} - \delta \times (X2_n^{IT} - X1_n^{IT}) \text{ (Eq)[II, 26]}$$

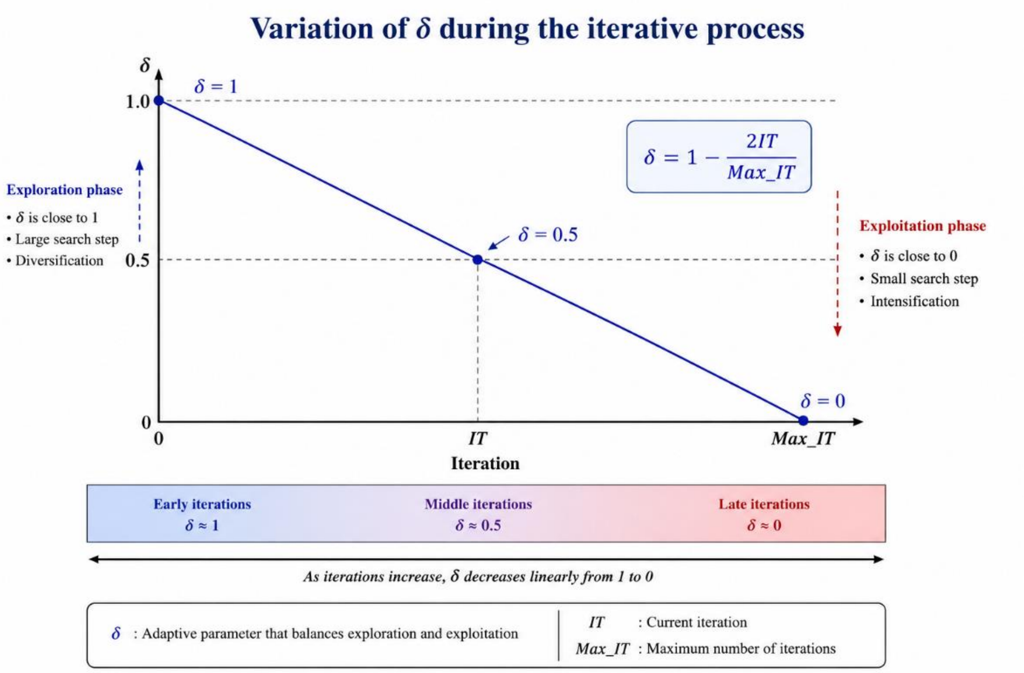

Figure II.3: *Variation of δ during the iterative process*

In these formulations, r_1 and r_2 are uniform random numbers that maintain the stochastic nature of the population's evolution, preventing the deterministic collapse of the search space.

The Trap Avoidance Operator (TAO)While the NRSR is highly effective for exploiting smooth regions of the search space, complex optimization landscapes are often riddled with local optima traps. NRBO incorporates the Trap Avoidance Operator (TAO) to provide the population with a "jump" mechanism to escape these traps. If a random number is less than the deciding factor (DF, typically 0.6), the position is radically updated to explore a new region [15].

$$= \begin{cases} x_n^{IT+1} + \theta_1 \times (\mu_1 \times x_b - \mu_2 \times x_n^{IT}) + \theta_2 \times \delta \times (\mu_1 \times \text{Mean}(X^{IT}) - \mu_2 \times x_n^{IT}) & \text{if } \mu_1 < 0.5 \\ x_b + \theta_1 \times (\mu_1 \times x_b - \mu_2 \times x_n^{IT}) + \theta_2 \times \delta \times (\mu_1 \times \text{Mean}(X^{IT}) - \mu_2 \times x_n^{IT}) & \text{otherwise} \end{cases} \quad (\text{Eq })[\text{II}, 27]$$

$$x_n^{IT+1} = x_{TAO}^{IT} \ (\text{Eq })[\text{II}, 28]$$

The stochastic nature of TAO is controlled by random variables θ_1 (range -1 to 1) and θ_2 (range -0.5 to 0.5), as well as the coefficients μ_1 and μ_2:

$$\mu_1 = \beta \times 3 \times \text{rand} + (1 - \beta) \ (\text{Eq })[\text{II}, 29]$$

$$\mu_2 = \beta \times \text{rand} + (1 - \beta) \ (\text{Eq })[\text{II}, 30]$$

In this formulation, β is a binary variable that alternates based on a probability threshold, allowing the TAO to act as both a global explorer and a local refiner.

Algorithm: Pseudocode of Newton-Raphson-Based Optimizer (NRBO)

Algorithm 1: Pseudocode of Newton-Raphson-Based Optimizer (NRBO)

Input: Population size N, maximum iterations Max_IT, problem dimension D, lower bound lb, upper bound ub, deciding factor DF

Output: Best solution X_{best} and its fitness value f_{best}

Initialization Phase:

1. Initialize the population X_i randomly:
   $$X_{i,j} = lb_j + rand \times (ub_j - lb_j)$$
   where $i = 1, 2, \dots, N$ and $j = 1, 2, \dots, D$.
2. Evaluate the fitness value $f(X_i)$ for each solution.
3. Determine:
   X_{best} = best solution
   X_{worst} = worst solution
4. Set $IT = 1$

Main *Iterative* *Process:*

5. **While** IT $\leq$ Max_IT **do**
   - **For** each solution X_i **do**
     - **For** each dimension $j = 1, 2, \dots, D$ **do**
       - Calculate the adaptive parameter: $\delta = 1 - (2 \times IT / \text{Max\_IT})$
       - Calculate the search step: $\Delta x = rand \times |X_{best} - X_i|$
       - Apply the Newton–Raphson Search Rule (NRSR): $NRSR = randn \times \frac{((X_{best} - X_{worst}) \times \Delta x)}{(2 \times (X_{best} + X_{worst} - 2X_i)}$
       - Update the current position: $X_i^{new} = X_i + \delta \times NRSR$
     - **End For**
     - Apply the Trap Avoidance Operator (TAO):
     - **If** rand $< DF$ **then**
       - Generate $\theta_1 \in [-1, 1]$ and $\theta_2 \in [-0.5, 0.5]$
       - Update the solution: $X_i^{new} = X_i^{new} + \theta_1 \times (X_{best} - X_i) + \theta_2 \times (rand \times X_{best} - X_i)$
     - **End If**
     - Apply boundary control:
       - **If** $X_i^{new} < lb$, set $X_i^{new} = lb$
       - **If** $X_i^{new} > ub$, set $X_i^{new} = ub$
     - Evaluate $f(X_i^{new})$
     - **If** $f(X_i^{new}) < f(X_i)$ **then**
       - $X_i = X_i^{new}$
     - **End If**
   - **End For**
   - Update X_{best} and X_{worst}
   - $IT = IT + 1$

End While

Termination:

6. Return X_{best} and f_{best}

II. 9 Computational Complexity and Efficiency Analysis

The NRBO's ability to outperform both classical mathematical methods and biological metaheuristics is rooted in its efficient computational structure. The complexity of the algorithm's initialization phase is linear with respect to the population size (O(N)), while the evaluation and sorting of objective function values follow O(N + N log N). The critical phase of updating solution vectors and control parameters has a complexity of O(N×D), where D is the dimensionality of the problem [15].

***Table II.2**: Computational Complexity Analysis of NRBO and Classical Newton-Raphson Method*

Algorithmic Phase	Complexity	Determining Factors
Initialization	$O(N \times D)$	Population size (N) and dimensions (D).
Fitness Evaluation	$O(N \times f)$	Cost of the objective function (f).
Solution Update	$O(N \times D)$	Execution of NRSR and TAO rules.
Overall NRBO	$O(N \times IT \times D)$	Total iterations (IT), scale (N), dimensions (D).
Classical NRM	$O(D^3)$	Cubic cost of Hessian matrix inversion.

The comparative advantage of NRBO is most apparent in high-dimensional search spaces. While the classical Newton-Raphson Method suffers from the cubic growth of matrix inversion, NRBO maintains linear complexity with respect to dimensionality, making it suitable for modern large-scale applications such as machine learning hyperparameter tuning, structural engineering design, and telecommunications routing optimization [1].

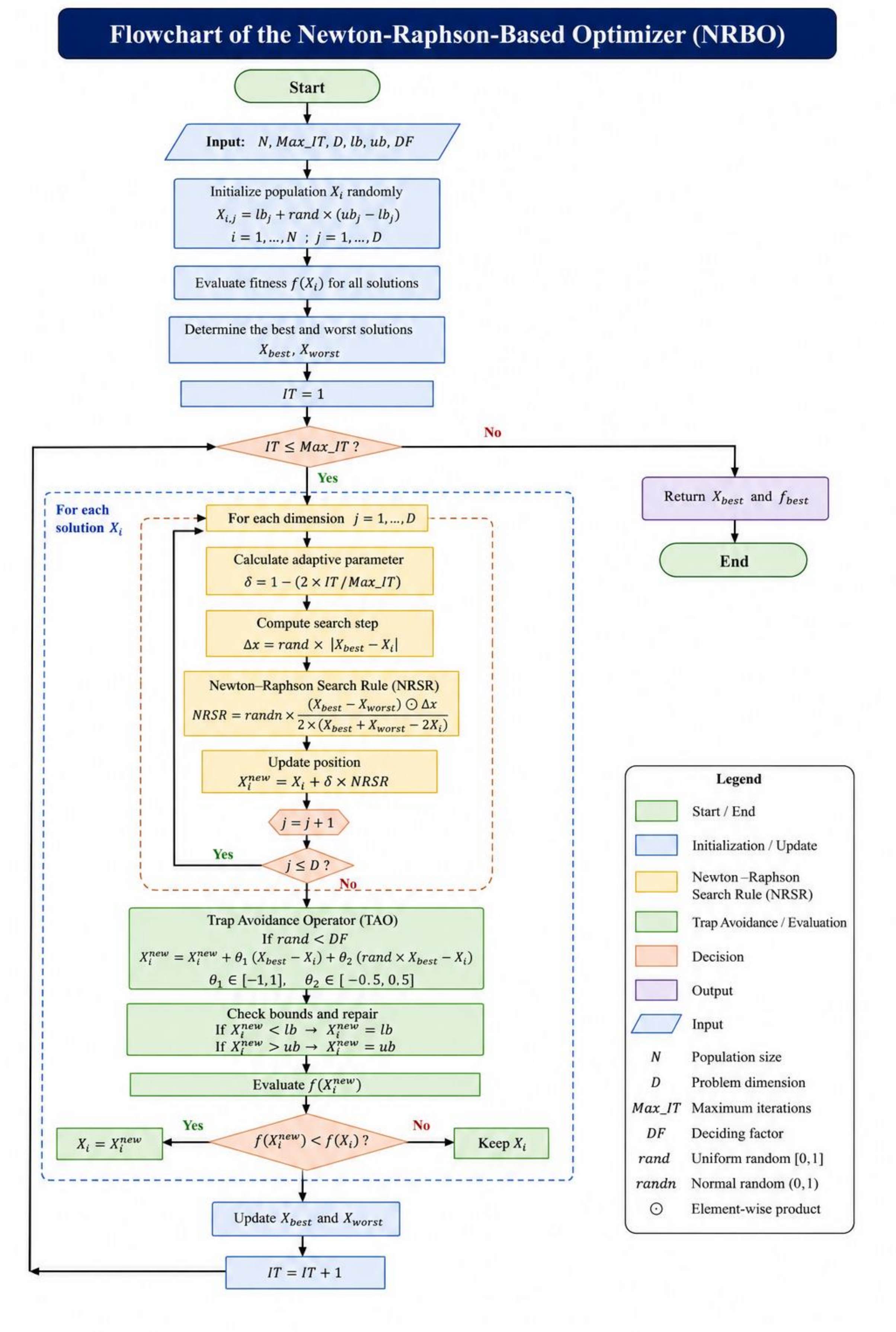

Figure II.4: *Flowchart of NRBO algorithm*

II. 10 Conclusion:

The Newton-Raphson-Based Optimizer (NRBO) represents a powerful and modern metaheuristic optimization technique inspired by the classical Newton-Raphson numerical method. By integrating mathematical principles with stochastic population-based search strategies, NRBO achieves an effective balance between exploration and exploitation during the optimization process. The algorithm mainly relies on the Newton-Raphson Search Rule (NRSR), which enhances convergence speed and improves the accuracy of the search process, and the Trap Avoidance Operator (TAO), which increases diversity and prevents premature convergence toward local optima.

One of the major strengths of NRBO lies in its adaptive behavior throughout the iterative process. The adaptive parameter δdynamically controls the transition from global exploration during the early iterations to local exploitation in the later stages. This mechanism enables the algorithm to efficiently investigate the search space while gradually focusing on promising regions to obtain high-quality solutions. In addition, NRBO demonstrates relatively low computational complexity compared with conventional Newton-based optimization methods, making it suitable for solving large-scale and nonlinear optimization problems.

Furthermore, NRBO has shown promising performance in various engineering and scientific applications, including optimization, machine learning, wireless communication systems, routing problems, and energy management. Its flexibility and robustness allow it to handle complex multidimensional problems with high efficiency and stability. Consequently, NRBO can be considered a reliable optimization framework capable of providing accurate and near-optimal solutions for challenging real-world applications. The integration of mathematical modeling with intelligent search mechanisms makes NRBO an important contribution to the field of modern optimization techniques.

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Chapter III:

Results and discussion

III.1 Introduction

With the increasing global demand for energy and the growing interest in renewable energy sources, solar energy has emerged as one of the most promising clean and sustainable alternatives. Photovoltaic (PV) systems convert solar radiation into electrical energy using solar cells, whose performance requires accurate mathematical modeling and analysis.

This work focuses on the study of the Single Diode Model (SDM) of photovoltaic cells and aims to improve the accuracy of parameter estimation using the Newton-Raphson-Based Optimization (NRBO) algorithm. This method enhances convergence speed and reduces the error between experimental and simulated results.

In this thesis, the electrical characteristics (I–V and P–V curves) of the PV system are analyzed, and a comparison between experimental data and simulation results is conducted to evaluate the effectiveness and reliability of the proposed model.

PHOTOVOLTAIC MODEL

Datasheets provide the PV solar cell or module manufacturers' V_{OC}, I_{SC}, P_{mp}, K_I, K, which were measured under standard test conditions (STCs). The STCs were at a temperature of 25 ◦C, irradiation of 1000 W⁄m 2 , and air mass of 1.50. A current–voltage (I −V) curve, as shown in Figure 1,isplotted for a PV solar cell or module with three remarkable points found in the datasheet, denoted by V_{OC}, Isc , MPP [45].

Under real environmental conditions, the datasheet values SC changed non-linearly, as illustrated in Figure 2. Therefore, cre- ating an interactive PV solar cell or module model is more convenient and reliable. Therefore, similarity can be achieved between the standard and real I −V curves. A PV cell is composed of two semiconductor layers (P and N) and a metal grid for wiring and connections. In the dark, it acts as a simple standard P–N junction diode that obeys the Shockley equation formulated in (1). In the presence of irradiation, solar energy frees up charge carriers and generates a photovoltaic current, which is denoted by I . An ideal PV solar cell model is composed of a current source and diode, as shown in Figure 3, so estimation can take place. The estimated current, denoted by I est PV , is indicated by an arrow in Figure 3 and can be written using Kirchhoff 's voltage law (KVL) at the node, as depicted in (2). The mathematical representation of the ideal PV solar cell model is represented by (3) and graphically in Figure 4.

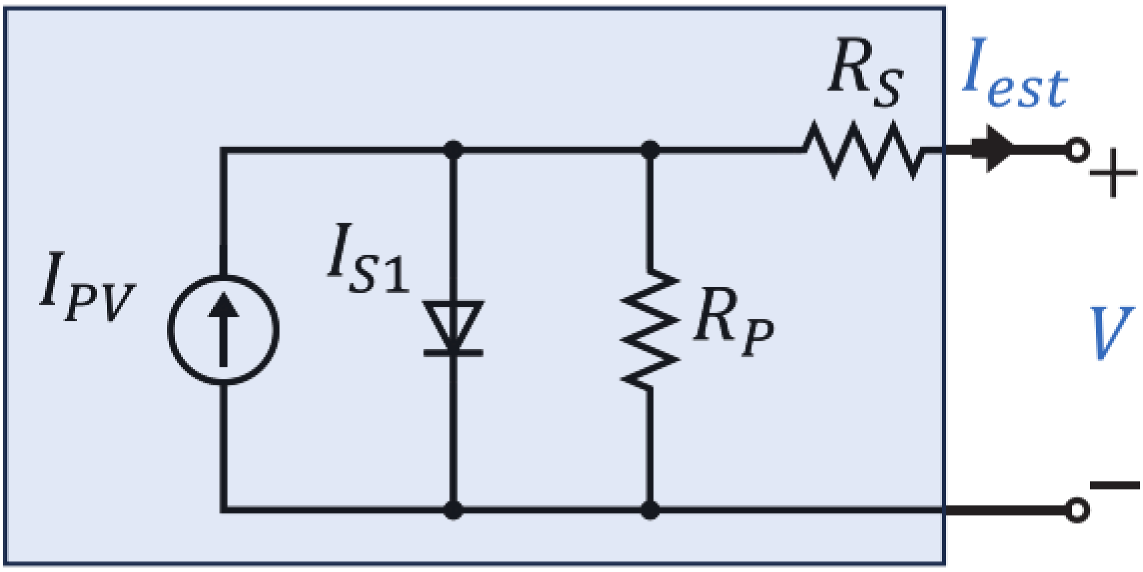

FIGURE 5 Single diode model representation.

The current in parallel resistance R of SDM of PV solar cell or module that is represented in Figure 5 can be calculated by (4), where I and V represent measured PV solar cell or module current and voltage respectively.

$$I_{R_P} = \frac{V + I \times R_S}{R_P}$$

The estimated current from the SDM for a PV solar cell or module can be formulated using Kirchhoff's current law which is presented in (5) and the total mathematical representation of the SDM is written in (6)[45].

$$I_{est} = I_{PV} - I_{D_1} - I_{R_P}$$

$$I_{est} = I_{PV} - I_{S_1}\left[exp\left(\frac{(V + I \times R_S)\ q}{n_1\ K\ T}\right) - 1\right] - \frac{V + I \times R_S}{R_P} \tag{6}$$

III.2 The convergence curve of the Newton–Raphson-Based Optimizer (NRBO)

Figure (III.1) represents the **convergence curve** of the Newton–Raphson-Based Optimizer (NRBO) during the optimization process. The horizontal axis corresponds to the number of iterations, while the vertical axis represents the fitness value obtained by the algorithm. [1]

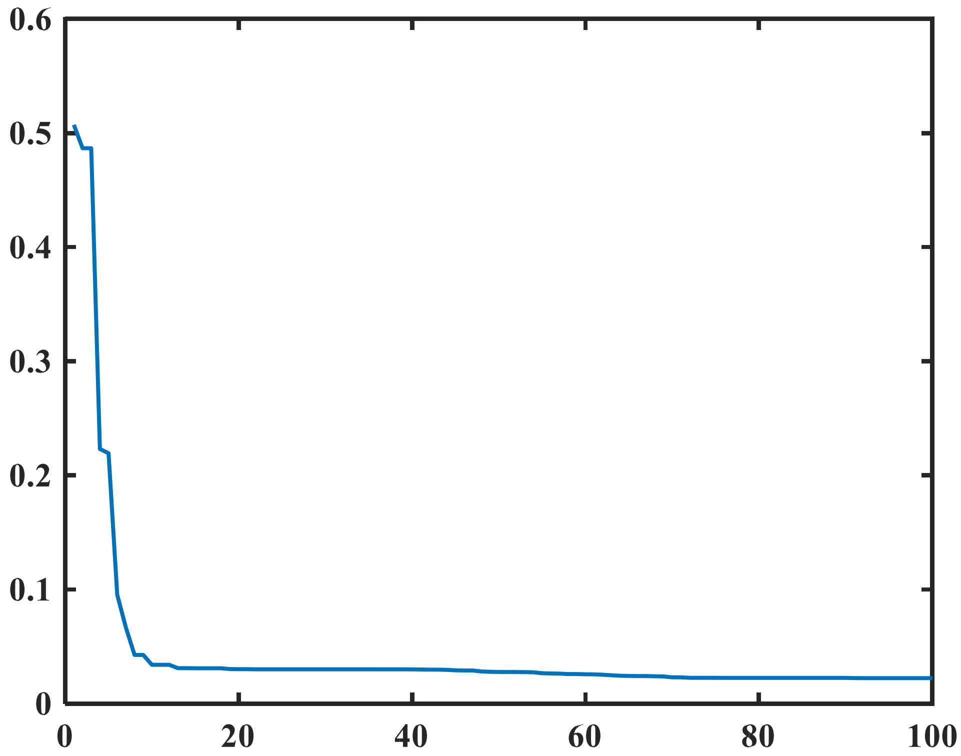

Figure (III.1): *Convergence curve of the Newton–Raphson-Based Optimizer (NRBO).*

III.2.1 Initial Exploration Phase and Rapid Fitness Reduction

At the beginning of the optimization process, the fitness value is relatively high (around 0.5), indicating that the initial randomly generated solutions are far from the optimal solution. During the first iterations, the curve decreases rapidly, which demonstrates the strong exploration capability of the NRBO algorithm and its efficiency in searching the solution space. [2]

III.2.2 Transition from Exploration to Exploitation

After approximately 10 iterations, the fitness value becomes significantly smaller and the convergence curve starts to stabilize. This behavior indicates that the algorithm gradually shifts from the exploration phase to the exploitation phase, where the search focuses on refining the best candidate solutions. [3]

III.2.3 Final Convergence and Optimization Stability

From iteration 20 onward, the curve decreases slowly and smoothly until reaching a very small fitness value close to zero at the final iterations. The absence of large oscillations confirms the stability of the optimization process and shows that the NRBO algorithm successfully converges toward an optimal or near-optimal solution. [4]

III.2.4 Performance Characteristics of the NRBO Algorithm

Overall, this convergence behavior demonstrates that the NRBO algorithm provides:

- Fast convergence speed,
- Stable optimization performance,
- Efficient balance between exploration and exploitation,
- High capability in minimizing the objective (fitness) function.

III.3 Current–Voltage (I–V) Characteristics of the PV Module

Figure (III.2) illustrates the current–voltage (I–V) characteristic of the photovoltaic (PV) module obtained using the optimized parameters identified by the NRBO algorithm. The horizontal axis represents the output voltage of the PV module, while the vertical axis corresponds to the output current. [5]

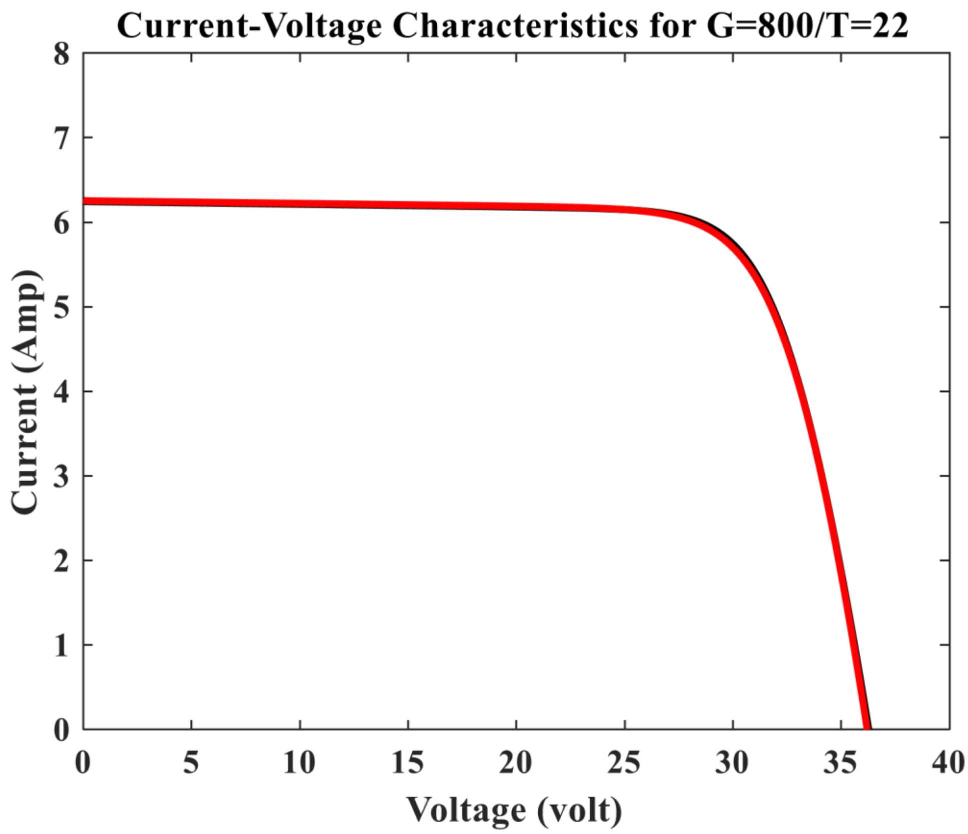

Figure (III.2): I-V Curve

III.3.1 Short-Circuit Current Region

At low voltage values, the PV module delivers an almost constant current of approximately 6.2 A, which corresponds to the short-circuit current region. This behavior indicates that the photovoltaic system is capable of supplying a stable current under low-load conditions. [6]

III.3.2 Constant Current Operating Region and Knee Point Formation

As the voltage increases, the current remains nearly constant over a wide operating range, demonstrating the normal operating behavior of a healthy photovoltaic module. Around the voltage range of 30–35 V, the curve begins to decrease rapidly, representing the knee region of the I–V characteristic. This region is particularly important because it contains the maximum power point (MPP) of the photovoltaic system. [7]

III.3.3 Open-Circuit Voltage Region

Beyond this region, the current drops sharply toward zero as the voltage approaches the open-circuit voltage (Voc), which is approximately 36–37 V in this case. This phenomenon reflects the physical limitation of the PV module when operating near open-circuit conditions. [8]

III.3.4 Model Validation Through Experimental Comparison

The close overlap between the black and red curves indicates a strong agreement between the experimental data and the estimated model generated using the NRBO algorithm. This confirms the accuracy and effectiveness of the proposed optimization approach in identifying the photovoltaic parameters and reproducing the electrical behavior of the PV module with high precision.

III.4 Power–Voltage (P–V) Characteristics of the PV Module

Figure below represents the power–voltage (P–V) characteristic of the photovoltaic (PV) module obtained using the optimized parameters identified by the NRBO algorithm. The black curve corresponds to the experimental data, while the red curve represents the estimated model generated by the optimization process. [9]

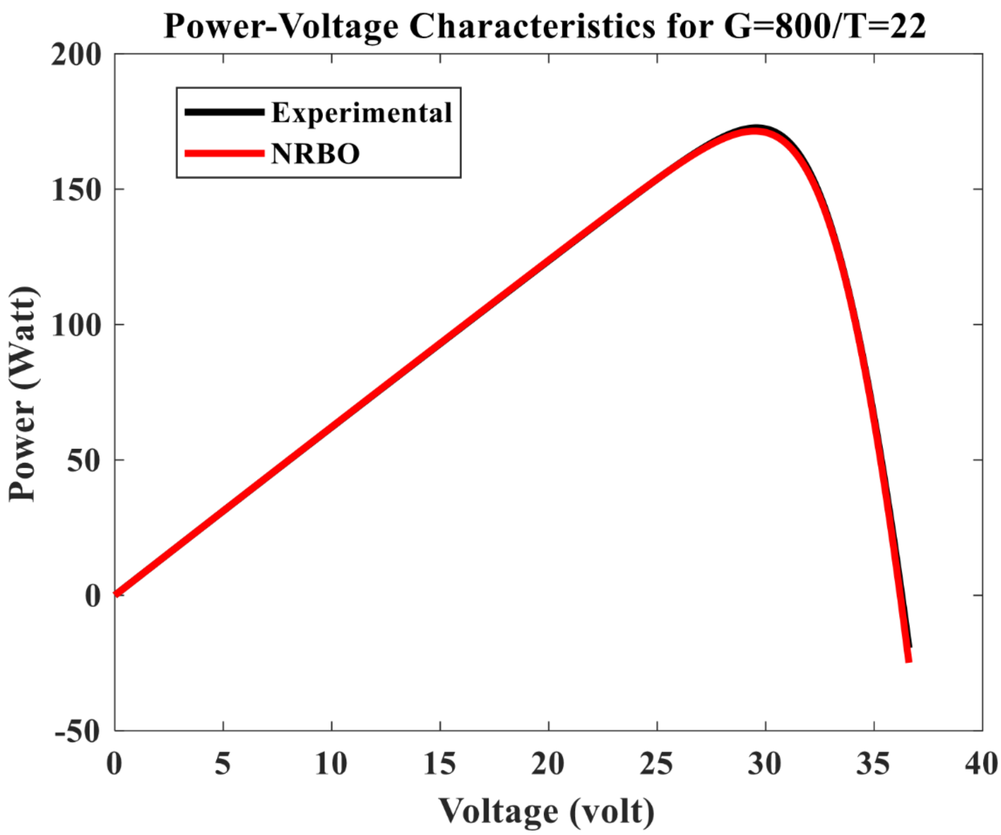

Figure (III.3): ***P-V Curve***

III.4.1 Power Evolution with Increasing Voltage

At low voltage levels, the output power is close to zero because the voltage is very small despite the presence of current. As the voltage increases, the output power rises almost linearly due to the simultaneous increase in both voltage and power generation capability of the photovoltaic module.

III.4.2 Maximum Power Point (MPP) Analysis

The curve reaches its maximum value around 30 V, which corresponds to the Maximum Power Point (MPP) of the PV system. At this operating point, the photovoltaic module delivers its highest power output, estimated at approximately 170–175 W. This region is particularly important in photovoltaic applications because MPPT (Maximum Power Point Tracking) techniques aim to operate the system continuously around this optimal point.

III.4.3 Power Reduction Near Open-Circuit Conditions

Beyond the MPP region, the output power decreases rapidly as the voltage approaches the open-circuit voltage. This behavior occurs because the current collapses sharply at high voltage values, resulting in a significant reduction in generated power.

III.4.4 Accuracy Assessment of the NRBO-Based PV Model

The strong overlap between the experimental and NRBO-estimated curves demonstrates the excellent accuracy of the proposed optimization algorithm in reproducing the real electrical behavior of the photovoltaic module. The very small deviation between both curves confirms that the NRBO algorithm successfully identifies the optimal PV parameters and provides a highly reliable photovoltaic model. [10]

Conclusion

In conclusion, the Single Diode Model proves to be an effective approach for representing the behavior of photovoltaic cells, especially when combined with advanced optimization techniques such as the NRBO algorithm. The obtained results demonstrate that NRBO significantly improves parameter estimation accuracy and reduces the discrepancy between experimental and simulated data.

Furthermore, a strong agreement was observed between the computed (I–V and P–V) curves and the experimental measurements, confirming the reliability of the proposed model.

These findings open perspectives for future research, particularly in developing more complex models or integrating artificial intelligence techniques to further enhance modeling accuracy and photovoltaic system efficiency.

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Conclusion

General Conclusion

The increasing demand for clean and sustainable energy sources has significantly accelerated research efforts in the field of photovoltaic systems. However, the accurate modeling and parameter identification of photovoltaic panels remain essential challenges due to the nonlinear behavior of PV characteristics and their sensitivity to environmental conditions such as temperature and solar irradiance. Consequently, the use of advanced optimization techniques has become indispensable for improving the accuracy and reliability of photovoltaic models.

In this dissertation, the Newton–Raphson-Based Optimizer (NRBO) was investigated and applied for the optimization of photovoltaic panel parameters. The study first introduced the theoretical foundations of photovoltaic systems and the mathematical modeling of solar panels using the single-diode model. Subsequently, the operating principles and mathematical formulation of the NRBO algorithm were presented in detail, including the initialization process, the Newton–Raphson Search Rule (NRSR), and the Trap Avoidance Operator (TAO).

The practical implementation of the NRBO algorithm was carried out using MATLAB software in order to estimate the optimal photovoltaic parameters. The obtained simulation results demonstrated the effectiveness of the proposed optimization technique in minimizing the fitness function and accurately reproducing the electrical behavior of the photovoltaic module. The convergence curve showed a rapid decrease in the fitness value during the first iterations, indicating the fast convergence capability of the NRBO algorithm. Furthermore, the close agreement between the experimental and estimated I–V and P–V characteristic curves confirmed the accuracy and robustness of the identified photovoltaic model.

The obtained results clearly demonstrate that the NRBO algorithm provides an efficient balance between exploration and exploitation mechanisms, allowing it to converge toward high-quality optimal solutions with good stability and reduced computational error. Therefore, the proposed optimization approach can be considered a promising technique for photovoltaic parameter estimation and renewable energy applications.

As future perspectives, this work may be extended by integrating more advanced photovoltaic models, considering partial shading conditions, incorporating temperature and irradiance variations, or comparing the performance of NRBO with other modern metaheuristic optimization algorithms such as PSO, GWO, and GA. Moreover, the proposed approach could also be combined with intelligent control strategies and Maximum Power Point Tracking (MPPT) techniques to further improve the efficiency and performance of photovoltaic energy systems.

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