



People's Democratic Republic of Algeria
Ministry of Higher Education and
Scientific Research



Echahid Hamma Lakhdar University of El-Oued

Faculty of Science and Technology Major: Electrical Engineering

End of study dissertation

Presented for graduation from

ACADEMIC MASTERS

In: Telecommunication

Specialty: Telecommunication systems

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Theme

**Exploring the Newton-Raphson-Based Optimizer:
A Novel Population-Based Metaheuristic for
Continuous Optimization and MANET Routing**

In front of the jury composed of:

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2024-2025

Dedication

All praise is due to Allah, who has blessed us with knowledge and wisdom, and made the pursuit of learning a light that guides the hearts of His servants.

With grateful hearts and minds enriched by knowledge, we humbly dedicate this modest work to:

Our beloved family, our anchor and lifelong support,

Who gifted us boundless love and encouragement roots that grounded us in strength, and wings that carried us toward success.

To our honorable teachers,

Who ignited within us the flame of knowledge and instilled the values of excellence, becoming beacons that illuminated our paths to achievement.

To our dear classmates and friends,

I extend my deepest gratitude to you, my cherished companions, who made this journey extraordinary with your unwavering support and sincere hearts. Your encouragement, collaboration, and priceless friendship were the driving force that helped me overcome challenges and celebrate triumphs. The beautiful memories we've shared will forever remain engraved in my heart, and I thank you from the depths of my soul for every cherished moment we spent together.

To all who extended a helping hand,

Whether through a word of encouragement, wise guidance, or a presence that inspired hope—this work is the fruit of your belief in us and the light of your insight that guided our way.

To you, we offer our sincerest emotions and sweetest memories.

Berrouk Khadra

Lakmouta Cheima

Abid Mohamed

Summary

This master's thesis explores the application of the Newton-Raphson-Based Optimization (NRBO) metaheuristic algorithm to improve routing protocols in mobile ad hoc networks (MANETs). MANETs are decentralized, self-organizing wireless networks where mobile nodes dynamically establish connections without relying on fixed infrastructure. Efficient routing protocols are critical in such environments, as they determine how data packets are forwarded to ensure reliable communication.

By considering routing in MANETs as an optimization problem, this study introduces NRBO as an innovative approach for identifying optimal routing paths. The thesis thoroughly examines the challenges of optimization in MANETs and presents NRBO as a promising solution to enhance routing efficiency.

The NRBO is firstly evaluated with various benchmark functions, The proposed NRBO-based routing protocol is then tested through different simulations under diverse network scenarios, including varying network sizes and node mobility patterns. The results indicate that the NRBO-based protocol successfully discovers high-quality routes, improving data delivery reliability and efficiency while maintaining low computational costs. Furthermore, the algorithm demonstrates strong adaptability, performing well in both small and large-scale MANET deployments.

Keywords: MANET, NRBO, optimization, metaheuristic, routing protocol.

المخلص

تعرض رسالة الماجستير هذه تطبيق خوارزمية التحسين القائم على نيوتن-رافسون (NRBO) الارتقائية لتحسين بروتوكولات التوجيه في الشبكات المتنقلة المخصصة (MANETs). شبكات MANETs هي شبكات لاسلكية لا مركزية وذاتية التنظيم، حيث تنشئ العقد المتنقلة اتصالات ديناميكياً دون الاعتماد على بنية تحتية ثابتة. تُعد بروتوكولات التوجيه الفعالة حاسمة في مثل هذه البيئات، لأنها تحدد كيفية إعادة توجيه حزم البيانات لضمان اتصال موثوق.

من خلال اعتبار التوجيه في شبكات MANETs مشكلة تحسين، تقدم هذه الدراسة NRBO كنهج مبتكر لتحديد مسارات التوجيه المثلى. تتناول الرسالة بشكل شامل تحديات التحسين في شبكات MANETs وتقدم NRBO كحل واعد لتعزيز كفاءة التوجيه.

تم تقييم NRBO أولاً باستخدام دوال معيارية مختلفة. ثم تم اختبار بروتوكول التوجيه المقترح القائم على NRBO من خلال محاكاة مختلفة في سيناريوهات شبكة متنوعة، بما في ذلك أحجام الشبكة المختلفة وأنماط حركة العقد. تشير النتائج إلى أن البروتوكول القائم على NRBO يكتشف بنجاح مسارات عالية الجودة، مما يحسن موثوقية وكفاءة تسليم البيانات مع الحفاظ على تكاليف حسابية منخفضة. علاوة على ذلك، تُظهر الخوارزمية قدرة قوية على التكيف، حيث تعمل بشكل جيد في شبكات MANETs صغيرة وكبيرة الحجم.

، تحسين، ميناهوريستيك، بروتوكول التوجيه NRBO، MANET: الكلمات المفتاحية

Here's the translation of the keywords:

الكلمات المفتاحية: الشبكات المتنقلة المخصصة، التحسين القائم على نيوتن-رافسون، التحسين، ميناهوريستيك / الخوارزمية الارتقائية، بروتوكول التوجيه

Résumé

Ce mémoire de master explore l'application de l'algorithme métaheuristique d'Optimisation Basée sur Newton-Raphson (NRBO) pour améliorer les protocoles de routage dans les réseaux ad hoc mobiles (MANETs). Les MANETs sont des réseaux sans fil décentralisés et auto-organisés où les nœuds mobiles établissent dynamiquement des connexions sans dépendre d'une infrastructure fixe. Des protocoles de routage efficaces sont essentiels dans de tels environnements, car ils déterminent la manière dont les paquets de données sont acheminés pour assurer une communication fiable.

En considérant le routage dans les MANETs comme un problème d'optimisation, cette étude introduit le NRBO comme une approche innovante pour identifier des chemins de routage optimaux. La thèse examine en détail les défis de l'optimisation dans les MANETs et présente le NRBO comme une solution prometteuse pour améliorer l'efficacité du routage.

Le NRBO est d'abord évalué avec diverses fonctions de référence. Le protocole de routage proposé basé sur le NRBO est ensuite testé à travers différentes simulations sous divers scénarios de réseau, y compris des tailles de réseau et des schémas de mobilité des nœuds variables. Les résultats indiquent que le protocole basé sur le NRBO découvre avec succès des routes de haute qualité, améliorant la fiabilité et l'efficacité de la livraison des données tout en maintenant des coûts de calcul faibles. De plus, l'algorithme démontre une forte adaptabilité, fonctionnant bien dans les déploiements MANETs à petite et à grande échelle.

Mots-clés : MANET, NRBO, optimisation, métaheuristique, protocole de routage.

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Abbreviations

LP: linear programming

NLP: nonlinear programming

GP: geometric programming

QP: quadratic programming

NRBO: Newton-raphson-based optimizer

NRSR: Newton-Raphson Search Rule

NRM: Newton-Raphson Method

TAO: : Trap Avoidance Operator

ACO : Ant Colony Optimization

TS : The Tabu Search

SA : Simulated Annealing

PSO : Particle Swarm Optimisation

GA : Genetic Algorithms

MH: Metaheuristic

MANETs: Mobile Ad Hoc Networks

LANs: Local Area Networks

WANETs: Wireless Ad Hoc Networks

IOT: Internet of Things

WSNs: Wireless Sensor Networks

VANETs: Vehicular Ad hoc Networks

IVANET: Infrastructure-less Vehicular Ad hoc Network

SPAN: Smartphone Ad hoc Network

In VANETs: Intelligent Vehicular Ad Hoc Networks

ITS: Intelligent Transportation Systems

RSUs: Roadside Units

V2V: Vehicle-to-Vehicle

V2R: Vehicle-to-Roadside

PANs: Personal Area Networks

MPN: Mars Proximity Network

IPANs: Inter-Planetary Area Networks

MAC: Medium Access Control

HANETs: Heterogeneous Ad Hoc Networks

OLSR: Optimized Link State Routing

DSDV: Destination Sequenced Distance Vector

GSR: Global State Routing

WRP: Wireless Routing Protocol

DT: Distance Table

RT: Routing Table

LCT: Link-Cost Table

MRL: Message Retransmission List

TORA: Temporally Ordered Routing Algorithm

LAR: Location-Aided Routing

DSR: Dynamic Source Routing

AODV: Ad-hoc On-Demand Distance Vector Routing

ABR: Associativity-Based Routing

LMR: Lightweight Mobile Routing

RREQ: Route Reques

RRER: Route Error

ZRP: Zone Routing Protocol

MITM: Man-in-the-Middle

General introduction

Optimization is a systematic approach used to identify the best possible values for a set of variables, given specific constraints, in order to maximize or minimize a desired objective function. The difficulty and feasibility of solving an optimization problem depend largely on the properties of the objective function and its constraints such as whether they are linear, differentiable, or continuous. This process is essential in addressing real-world challenges that require efficient resource allocation amid uncertainties, often drawing inspiration from natural systems and empirical knowledge.

It is also considered Optimization techniques are ways to find the best solution to a problem. They are divided into two main types: exact methods, which give the best possible answer, and approximate methods, which give a good answer in less time. These methods help solve problems in many areas like engineering, business, and computer science.

In this context, it appears Metaheuristics are flexible optimization techniques designed to find near-optimal solutions for complex search and optimization problems. They use strategies like randomness and iterative improvement to efficiently explore vast solution spaces. While they don't guarantee the absolute best solution, they provide practical and computationally efficient approaches particularly for problems where traditional methods fail or become too expensive. Thanks to their adaptability, metaheuristics are widely applied across various fields to solve otherwise intractable challenges.

One prominent domain where optimization and metaheuristics can be effectively applied is in Mobile Ad Hoc Networks (MANETs) are self configuring, infrastructure-free wireless networks composed of mobile devices that dynamically establish temporary connections. These networks are particularly valuable in scenarios where fixed infrastructure is absent or impractical, such as military operations, disaster relief, emergency communications, and remote collaborative tasks. Their key advantages include rapid deployment, adaptability to changing topologies, and scalability in challenging environments.

A key feature of MANETs is their ability to maintain connectivity despite node mobility, allowing devices to join, leave, or move without manual configuration. While enabling efficient peer-to-peer communication, they face challenges such as limited bandwidth, security vulnerabilities, and the need for dynamic routing. Routing protocols ensure optimal data transmission by evaluating network conditions like topology and QoS. This thesis examines the application of the Newton-Raphson-Based Optimization (NRBO) method in MANETs, which iteratively uses tangent-based linear approximations to optimize routing.

By inspiring from Newton-Raphson technique, that uses both the function's value and its derivative, NRBO achieves high convergence rates, making it effective for optimization tasks. Its efficacy has been demonstrated across diverse fields, such as engineering design, image processing, and wireless communications, suggesting its potential for enhancing MANET performance. Given the inherent difficulties in Mobile Ad Hoc Networks (MANETs), this research introduces a novel NRBO driven routing algorithm, designated as Optimal Routing in MANETs Using NRBO. The methodology capitalizes on the self-adjusting and collective decision-making properties of the NRBO technique to refine routing protocols, ensuring efficient path discovery in dynamic network topologies. The adaptive framework of

the proposed solution is expected to improve network performance while maintaining robustness against the fluctuating nature of MANETs.

This manuscript comprises three interrelated chapters, systematically organized as follows:

Chapter I: provides a general introduction to optimization problems and discusses the Newton-Raphson-Based Optimization (NRBO) principle as one of the methods used in this field.

Chapter II: presents a comprehensive review of Mobile Ad Hoc Networks (MANETs), examining their different classifications, network structures, fundamental features, practical applications, and the routing protocols utilized in such networks.

Chapter III introduces an innovative routing strategy utilizing MANET, outlining NRBO's methodology for identifying the most efficient path.

Finally, we recap the main discoveries and propose future perspectives.

Chapitre I : Optimization and Newton-Raphson-Based optimized Method

1.1. Introduction

1.2. Definition of Optimization problem

1.3. Statement of optimization problem

1.4. Classification of optimization problems

1.5. Optimization techniques

1.6. The metaheuristics

1.7. Classification of metaheuristics

1.8. metaheuristics Techniques

1.9. Application of metaheuristics

1. 10. Newton-raphson-based optimizer (NRBO)

1.11. Conclusion

I.1.Introduction

An optimization problem is a computational task that involves identifying the optimal solution among all possible alternatives. Specifically, it aims to determine a feasible solution that either minimizes or maximizes the value of a given objective function.

Traditional optimization approaches frequently prove inadequate when tackling intricate problems. Metaheuristic algorithms emerge as a powerful alternative to overcome this limitation. As flexible optimization methodologies, these techniques deliver effective solutions for complex problem-solving scenarios. Inspired by natural processes or heuristic strategies, metaheuristics demonstrate superior capabilities in both exploring and exploiting the solution space, rendering them applicable across diverse domains. The evolution of metaheuristic algorithms has been shaped by progress in multiple disciplines, encompassing computer science, operations research, numerical analysis, game theory, mathematical economics, control theory, and combinatorial mathematics.

In 2023, Ravichandran Sowmya and his colleagues Manharan Premhumar and Pradeep Jangir developed a novel optimization algorithm called the Newton Raphson-Based Optimizer (NRBO), which is based on the Newton-Raphson method. The NRBO employs search mechanisms such as the Newton-Raphson Search Rule and the Trap Avoidance Operator to enhance the search process and prevent convergence to local optima. This algorithm combines the principles of the classical Newton-Raphson method with modern optimization techniques to achieve more accurate and efficient results. [1]

This chapter explores optimization problems and techniques, including metaheuristic methods that mimic natural processes. The Newton-Raphson-Based optimization (NRBO) technique is highlighted, with a detailed discussion of its conceptual origins and mathematical modeling.

I.2 Definition of optimization problem

The structural properties of the objective function and constraints—with respect to the decision variables—determine the computational tractability of an optimization problem, influencing both the choice of solution algorithms and the guarantee of reaching a true optimal solution.

Optimization has always been an inherent part of daily life since ancient times. To cope with constraints, individuals must devise solutions that adhere to resource limitations while navigating uncertainties and incomplete knowledge of certain problems.

Many solutions initially stem from observations of nature. Over time, knowledge evolves by building upon these natural observations and accumulated past experiences. In daily practice, existing solutions are continually tested and may be replaced by more efficient alternatives to enhance problem-solving performance. Researchers frequently employ single-objective optimization when addressing real-world problems.

A more effective approach to problem-solving can often be achieved by incorporating multiple objectives. Multi-objective optimization involves simultaneously optimizing two or more

conflicting objectives while satisfying given constraints. An optimal solution in this context is one that is not dominated by any other solution within the search space, known as Pareto optimal solution [2,3]

I.3. Statement of an optimization problem

The optimization problem involves determining the optimal values of the decision variables that either minimize or maximize the objective function, subject to the given constraints.

An optimization problem can be stated as follows

$$\text{Find } X = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ \vdots \\ x_p \end{Bmatrix} \text{ Which minimizes } f(x) \tag{Eq I.1}$$

Subject to the constraints

$$g_j(x) < 0, j = 1, 2, \dots, m \tag{Eq I.2}$$

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

Here, X represents an a -dimensional vector referred to as the design vector, $f(x)$ is defined as the objective function, and $g(x)$ along with $h(x)$ are termed the inequality constraints and equality constraints, respectively. Note that the number of variables (a) and the number of constraints (m) for inequalities and (p) for equalities are not inherently dependent on one another.

The problem presented in Eq. (I.1) is referred to as a constrained optimization problem. In contrast, some optimization problems involve no constraints and can be formulated as:

$$\text{Find } X = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ \vdots \\ \vdots \\ x_p \end{Bmatrix} \text{ Which minimizes } f(x) \tag{Eq I.4}$$

Such problems are called unconstrained optimization problems.

Figure I.1 illustrates several local maxima and minima. Point A represents a strict (strong) local maximum, whereas Point B is a weak local maximum due to the existence of infinitely many distinct values of (x) that yield the same function value ($f(x^*)$). Point D corresponds to the global maximum. On the other hand, Point C is a strict local minimum, yet it exhibits a discontinuity in the derivative ($f'(x^*)$), meaning the stationary condition does not hold smoothly at this point. [4]

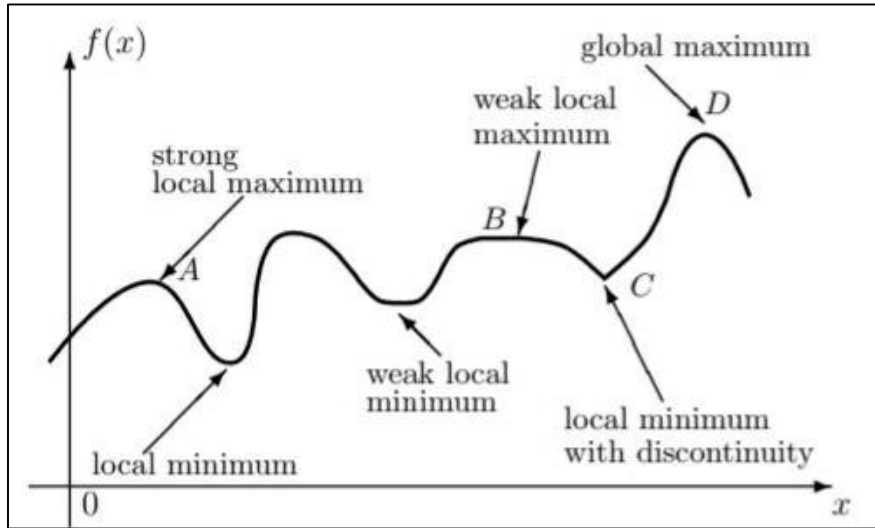


Figure I.1. Strong and weak maxima and minima [5]

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.

1.4 CLASSIFICATION OF OPTIMIZATION PROBLEMS

There are multiple classification methods for optimization problems, as detailed in the following. [4]

1.4.1 Classification Based on the Existence of Constraints

As previously mentioned, optimization problems can be categorized as either constrained or unconstrained, based on the presence or absence of constraints in the problem formulation.

1.4.2 Classification Based on the Nature of the Design Variables

Optimization problems can be broadly classified into two main types based on the nature of their design variables:

1. Parameter Optimization Problems: In this category, the goal is to determine the optimal values of a set of design parameters that minimize (or maximize) a given objective function while satisfying specified constraints. Here, the design variables are typically discrete or fixed parameters.
2. Functional Optimization Problems: This category involves finding optimal design parameters that are themselves continuous functions of another independent variable. The objective is to minimize (or maximize) a functional (a function of functions) subject to certain constraints.

Both categories are fundamental in optimization theory, with the first focusing on finite-dimensional parameter spaces and the second dealing with infinite-dimensional function spaces.

1.4.3 Classification Based on the Physical Structure of the Problem

This classification method groups optimization problems according to their inherent physical structure, distinguishing categories such as network optimization problems, graph-based problems, or permutation-related problems, each belonging to a distinct structural class.

1.4.4 Classification Based on the Nature of the Equations Involved

An essential classification of optimization problems is based on the mathematical nature of the objective function and constraint expressions. According to this criterion, optimization problems can be categorized into linear programming (LP), nonlinear programming (NLP), geometric programming (GP), and quadratic programming (QP) problems.

This classification is particularly valuable from a computational perspective, as numerous specialized methods have been developed to solve each class of problems efficiently. Consequently, a designer's first step should be to determine the problem's classification, as this often dictates the appropriate solution techniques to employ.

1.4.5 Classification Based on the Deterministic Nature of the Variables

Classification of Optimization Problems Based on Variable Nature

Optimization problems can be categorized into two main types depending on the nature of their variables:

1. Deterministic Programming

In deterministic programming problems, all variables and parameters (including design variables and preassigned parameters) are known with certainty and precisely defined, with no randomness involved. In other words, these problems can be modeled using fixed and well-defined values, allowing them to be solved using traditional optimization techniques such as linear or nonlinear programming.

2. Stochastic Programming

A stochastic programming problem is an optimization problem where some or all parameters (design variables and/or preassigned parameters) are probabilistic (non-deterministic or stochastic).

1.4.6 Classification Based on the Separability of the Functions

The classification of optimization problems into separable and nonseparable types is determined by the separability property of their objective and constraint functions.

1.4.7 Classification Based on the Number of Objective Functions

Depending on how many objective functions need minimization, optimization problems are classified as either single-objective or multiobjective programming problems.

1.5 Optimization techniques

Optimization methods for solving various types of optimization problems fall under the domain of mathematical optimization. These techniques can be broadly classified into two primary categories: exact methods and approximate (heuristic) methods. [5-7].

1.5.1. The exact techniques

Exact methods are rigorous techniques employed to solve optimization problems by identifying the globally optimal solution without resorting to approximations or heuristic assumptions. Unlike empirical approaches that depend on statistical estimations or heuristic rules, exact methods guarantee the determination of the true optimal solution.

These methods comprise diverse algorithmic strategies, classified according to the type of decision variables involved. For example, integer programming is applied to problems with discrete variables, whereas linear programming can handle both continuous and discrete variables. Nevertheless, these methods often involve high computational complexity, making them impractical for extremely large-scale or highly intricate problems.

1.5.2 Approximate Techniques

Approximation techniques, also known as heuristic or metaheuristic methods., are utilized when a problem's complexity makes an exhaustive search for all possible solutions impractical or only partially achievable.

While these methods do not ensure the discovery of an optimal solution, they provide computationally feasible and satisfactory solutions within a reasonable timeframe. They typically rely on guided search strategies, incorporating probabilistic approaches, heuristics, or evolutionary algorithms to explore the solution space more efficiently. Such techniques are particularly valuable for addressing large-scale optimization problems involving numerous variables or constraints.

I.6. The metaheuristics

Metaheuristics are powerful tools for solving difficult optimization problems, due to their ability to efficiently explore the search space. With more than 1222 publications in the scientific literature, according to Ka-shif et al. (2018), metaheuristics have been widely used in various fields.

These methods exhibit the following features:

- Stochasticity, which enables them to cope with the exponential growth of possibilities.
- Independence from gradient calculations, which can be problematic.
- Inspiration from natural sciences, such as physics, biology, and ethology.

Nevertheless, these methods also suffer from common limitations, including parameter tuning difficulties. [8-10]

I.7. Classification of metaheuristic

Metaheuristic algorithms can be categorized based on various criteria. The following classifications are commonly used .

1. Nature-inspired vs. non-nature-inspired: Metaheuristics can be distinguished based on their inspiration from natural processes. Nature-inspired metaheuristics include genetic algorithms, particle swarm optimization, and ant colony optimization, whereas non-nature-inspired metaheuristics comprise simulated annealing and tabu search.

2. Single-solution vs. population-based: Metaheuristics can be categorized based on whether they operate on a single solution or a population of solutions. Single-solution metaheuristics include simulated annealing and hill climbing, whereas population-based metaheuristics include genetic algorithms, particle swarm optimization, and ant colony optimization.

3. Deterministic vs. stochastic: Metaheuristics can be classified based on whether they employ deterministic or stochastic processes. Deterministic metaheuristics utilize deterministic processes to generate new solutions, as seen in hill climbing and deterministic annealing. In contrast, stochastic metaheuristics employ stochastic processes to generate new solutions, as seen in genetic algorithms and simulated annealing.

4. Trajectory-based vs. population-based: Metaheuristics can be categorized based on whether they focus on finding a single solution or multiple solutions. Trajectory-based metaheuristics focus on finding a single solution and use iterative improvement to refine that solution, as seen in hill climbing and simulated annealing. In contrast, population-based metaheuristics focus on finding multiple solutions and use a population of solutions to explore the search space, as seen in genetic algorithms and particle swarm optimization.

5. Local search-based vs. global search-based: Metaheuristics can be classified based on whether they focus on exploring the local search space or the global search space. Local search-based metaheuristics focus on finding solutions in the immediate vicinity of the current solution, as seen in hill climbing and tabu search. In contrast, global search-based metaheuristics focus on exploring the entire search space, as seen in genetic algorithms and ant colony optimization. [11]

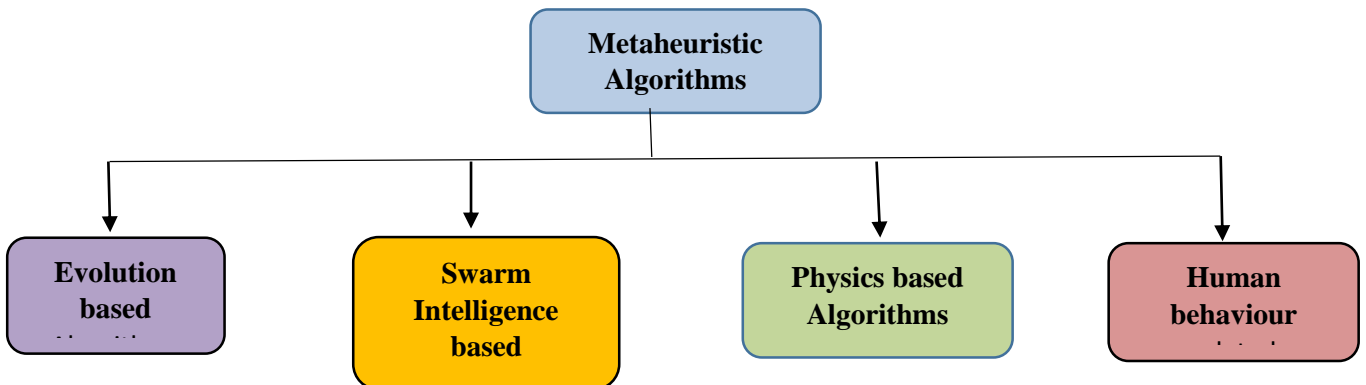


Figure I.2. Metaheuristic Algorithm classification [11]

I.8. Metaheuristics techniques

Numerous metaheuristic algorithms have been developed over the years, each with its strengths and weaknesses. some of the most well-known metaheuristic algorithms:

a) Genetic Algorithms (GA): GA is inspired by the principles of natural selection and genetics. It starts by generating an initial population of solutions randomly, and then evolves the population by applying operators such as selection, crossover, and mutation.

b) Particle Swarm Optimization (PSO): PSO is an algorithm for swarm intelligence that draws inspiration from the group behaviors of social creatures like fish schools and flocks of birds. A swarm of particles, each representing a potential solution to the optimization problem, is generated randomly.

c) Simulated Annealing (SA): SA is a stochastic optimization approach that draws inspiration from the metallurgical annealing process. The system's temperature is gradually lowered after an initial solution is generated randomly.

d) Tabu Search (TS): TS is a metaheuristic that draws inspiration from the concept of memory in human decision-making. It generates an initial solution randomly, and then uses operators such as swapping and reversing to search the neighborhood of the solution.

e) Ant Colony Optimization (ACO): ACO is a swarm intelligence method that is based on how ants navigate their environment to find the shortest path between their colony and a food source. An initial set of pheromone trails is generated randomly to indicate the quality of the solutions found so far.[11]

I.9. 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. [12-14]

I.10. Newton-raphson-based optimizer (NRBO)

Developed in 2023 by Ravichandran Sowmya, Manoharan Premkumar, and Pradeep Jangir, the Newton-Raphson-Based Optimizer (NRBO) is a novel metaheuristic algorithm that integrates the Newton-Raphson method with modern optimization techniques, this section presents the source inspiration of NRBO, its mathematical mode algorithm and flowchart.

I.10.1. Inspiration

Newton's method, also known as the Newton-Raphson Method (NRM), is a root-finding algorithm that utilizes the initial terms of the Taylor Series (TS) of a function $f(x)$ in the neighborhood of a presumed root to determine the root of the function. For polynomial functions $f(x)$, NRM is essentially analogous to Horner's method. The NRM commences with an initial point (x_0) and subsequently employs the TS evaluated at x_0 to identify an additional point in proximity to the previous solution. This iterative process is repeated until a satisfactory solution is obtained. The TS of $f(x)$ about the point $(x = x_0 + \epsilon)$ is represented as follows.[15-18]

$$f(x_0 + \epsilon) = f(x_0) + f'(x_0)\epsilon + \frac{f''(x_0)(\epsilon)^2}{2!} + \frac{f'''(x_0)(\epsilon)^3}{3!} + \dots \quad (\text{Eq I.5})$$

Preserving the second-order terms

$$f(x_0 + \epsilon) \approx f(x_0) + f'(x_0)\epsilon + \frac{f''(x_0)(\epsilon)^2}{2} \quad (\text{Eq I.6})$$

Equation (I.5) can be employed to determine the offset ϵ necessary to locate a point closer to the root originating from x_0 . By assuming $f(x_0 + \epsilon) = 0$ and solving Eq. (I.6) for ϵ , denoted as ϵ_0 , we obtain:

$$\epsilon_0 = -\frac{f(x_0)}{f'(x_0)} \quad (\text{Eq I.7})$$

Equation (I.7) represents a second-order refinement of the root's position. By setting $x_1 = x_0 + \epsilon_0$, the next estimate of the root can be determined, and this process can be iteratively repeated until convergence to the optimal root is achieved using Equation (I.8).

$$\epsilon_n = -\frac{f(x_n)}{f'(x_n)} \quad (\text{Eq I.8})$$

Unfortunately, this process can become unstable near a local maximum or a horizontal asymptote. Nevertheless, the method can be iteratively applied to find subsequent approximations, provided that a suitable initial position is chosen

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}, n = 1, 2, 3, \dots \quad (\text{Eq I.9})$$

In the Newton-Raphson Method (NRM), an approximate zero refers to an initial point x_0 that guarantees stable convergence of the algorithm.

4.10.2. Mathematical Model

The proposed NRBO algorithm defines the search trajectory by leveraging the Newton-Raphson Method (NRM) to identify the search region, utilizing two operators, namely **NRSR** and **TAO**, to systematically explore the search domain.

a: Initialization

Consider the following scenario: The optimization process is applied to an unconstrained single-objective optimization problem, defined as follows:

$$lb \leq x_j \leq ub, j = 1, 2, \dots, dim \tag{Eq I.10}$$

Here, $f(x)$ represents the fitness function to be minimized, x_j denotes the decision vector, dim represents the problem dimension, lb and ub denote the lower and upper bounds, respectively.

Similar to other metaheuristic (MH) algorithms, NRBO initializes its search for optimal solutions by generating an initial random population within the boundaries of the search space. Given that there are N_p populations, each comprising dim decision variables/vectors, the random population is generated using Eq. (I.11).

$$x_j^n = lb + rand \times (ub - lb), n = 1, 2, \dots, N_p \text{ and } j = 1, 2, \dots, dim \tag{Eq I.11}$$

where $x_{i,j}$ represents the j th dimensional position of the n th population, and $rand$ denotes a random number uniformly distributed between (0,1). Equation (I.12) presents the population matrix, which can be used to represent the populations with all their respective dimensions.

$$\begin{bmatrix} x_1^1 & x_2^1 & \dots & x_{dim}^1 \\ x_1^2 & x_2^2 & \dots & x_{dim}^2 \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{N_p} & x_2^{N_p} & \dots & x_{dim}^{N_p} \end{bmatrix} \tag{Eq I.12}$$

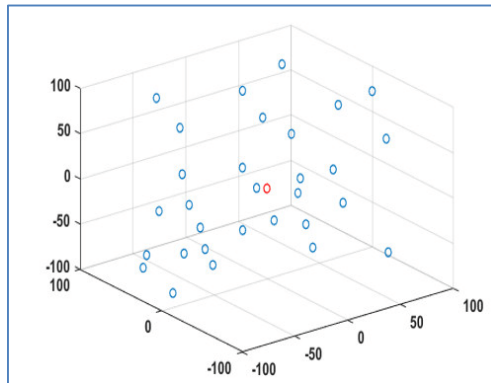


Figure I.3. Random initialization [19]

b: Newton-Raphson Search Rule (NRSR)

The NRSR operator is based on the Newton-Raphson Method (NRM), it is employed to ensure a more accurate exploration of the search space and yielding optimal solutions.

Inspiring from the NRM that initiates with a supposed initial solution and proceeds to the next location in a definite direction, the second-order derivative is determined using the Taylor Series (TS) approximation.

The TS for $f(x - \Delta x)$ and $f(x + \Delta x)$ is expressed as follows.

$$f = (x + \Delta x) = f(x) + f'(x_0)\Delta x + \frac{1}{2!}f''(x_0)\Delta x^2 + \frac{1}{3!}f'''(x_0)\Delta x^3 + \dots \quad (\text{Eq I.13})$$

$$f = (x - \Delta x) = f(x) - f'(x_0)\Delta x - \frac{1}{2!}f''(x_0)\Delta x^2 - \frac{1}{3!}f'''(x_0)\Delta x^3 + \dots \quad (\text{Eq I.14})$$

Through the subtraction/addition of Eq. (I.13) and Eq. (I.14), the derivative expressions for $f'(x)$ and $f''(x)$ are obtained as follows:

$$f'(x) = \frac{f(x+\Delta x) - f(x-\Delta x)}{2\Delta x} \quad (\text{Eq I.15})$$

$$f''(x) = \frac{f(x+\Delta x) + f(x-\Delta x) - 2f(x)}{\Delta x^2} \quad (\text{Eq I.16})$$

Substituting the expressions from Eq. (I.15) and Eq. (I.16) into Eq. (I.9) yields the updated position, which can be rewritten as follows.

$$x_{n+1} = x_n - \frac{(f(x_n+\Delta x) - f(x_n-\Delta x)) \times \Delta x}{2 \times (f(x_n+\Delta x) + f(x_n-\Delta x) - 2f(x_n))} \quad (\text{Eq I.17})$$

Given that the NRSR operator is intended to be the primary component of the Newton-Raphson-Based Optimization (NRBO), certain adjustments are necessary to manage the population-based search.

As a result of Eq. (I.17), the positions of x adjacent to each other are denoted by $x_n+\Delta x$ and $x_n-\Delta x$, respectively. This pair of neighboring positions is transformed into two other vectors in the population by the NRBO. Since $f(x_n)$ is a minimization problem, as depicted in Fig.I.4 position $x_n+\Delta x$ has an inferior fitness value than position x_n , whereas position $x_n-\Delta x$ has better fitness than position x_n . Consequently;

- ✓ the NRBO replaces position $x_n-\Delta x$ with position X_b , which has a better position in its neighborhood than position x_n ,
- ✓ while position $x_n+\Delta x$ is replaced by position X_w , which has a worse position in its neighborhood than position x_n .

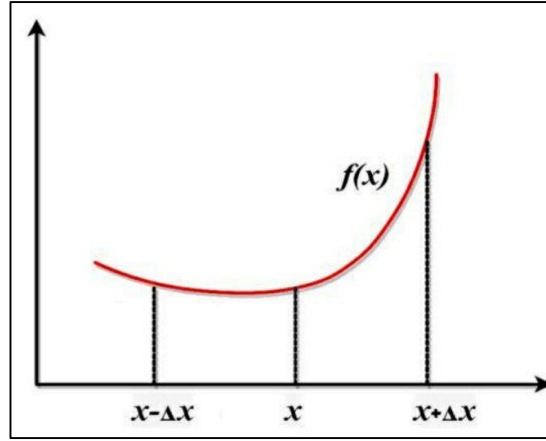


Figure. I.4. Location of the position $x[1]$

A further advantage of the proposed approach is that it utilizes the position (x_n) rather than its fitness ($f(x_n)$), thereby saving computational time. Subsequently, the proposed NRSR is expressed as follows:

$$NRSR = randn \times \frac{(X_w - X_b) \times \Delta x}{2 \times (X_w + X_b - 2 \times x_n)} \quad (\text{Eq I.18})$$

Where;

- $randn$ represents a normally distributed random number with a mean of 0 and a variance of 1,
- X_w denotes the worst position,
- X_b denotes the best position.

As a general guideline, the proposed algorithm must achieve a balance between diversification and intensification to discover optimal solutions within the search space and ultimately converge to the global solution. To further enhance the algorithm, an adaptable coefficient δ can be introduced. The expression for δ is presented in Eq. (I.19).

$$\delta = \left(1 - \left(\frac{2 \times IT}{Max_IT}\right)\right)^5 \quad (\text{Eq. I.19})$$

The current iteration is denoted by IT , and the maximum number of iterations is represented by $Max\ IT$. To strike a balance between exploration and exploitation phases, the parameter δ undergoes adaptive adjustments throughout the iterative process. The variation of δ across each iteration is depicted in Fig.I. 5 As per Eq. (I.19), the value of δ ranges from 1 to -1.

The expression for Δx in Eq. (I.18) is further elaborated in Eq. (I.20).

$$\Delta x = rand(1, dim) |X_b - X_n^{IT}| \quad (\text{Eq I.20})$$

where X_b is the best solution obtained so far, and $rand(1 : dim)$ is a random vector with dim decision variables. The modified (Eq.I.17), incorporating the NRSR, is rewritten as follows.

$$x_{n+1} = x_n - NRSR \quad (\text{Eq I.21})$$

The **exploitation** capabilities of the proposed NRBO are enhanced through the introduction of an additional parameter, ρ , which guides the population towards the optimal direction. The expression for ρ is presented as follows.

$$\rho = a \times (X_b - X_n^{IT}) + b \times (X_{r1}^{IT} - X_{r2}^{IT}) \quad (\text{Eq I.22})$$

In this formulation, a and b represent random numbers between (0,1), while r1 and r2 are randomly chosen integers from the population, with the condition that r1 and r2 are not equal. The position of the vector (x_n^{IT}) is subsequently updated using Eq. (I.23).

$$X1_n^{IT} = x_n^{IT} - \left(rand \times \frac{(X_w - X_b) \times \Delta x}{2 \times (X_w + X_b - 2 \times X_n)} \right) + (a \times (X_b - X_n^{IT}) + b \times (X_{r1}^{IT} - X_{r2}^{IT})) \quad (\text{Eq I.23})$$

The updated vector position $x1_n^{IT}$ is derived from x_n^{IT} . By integrating the NRM, as proposed by [13]; [14], the NRSR is refined. Subsequently, Eq. (I.17) is reformulated and presented as follows.

$$NRSR = randn \times \frac{(y_w - y_b) \times \Delta x}{2 \times (y_w + y_b - 2 \times x_n)} \quad (\text{Eq I.24})$$

$$y_w = r_1 \times (\text{Mean}(Z_{n+1} + x_n) + r_1 \times \Delta x) \quad (\text{Eq I.25})$$

$$y_b = r_1 \times (\text{Mean}(Z_{n+1} + x_n) - r_1 \times \Delta x) \quad (\text{Eq I.26})$$

$$Z_{n+1} = x_n - randn \times \frac{(X_w - X_b) \times \Delta x}{2 \times (X_w + X_b - 2 \times x_n)} \quad (\text{Eq I.27})$$

A random number r1 between (0,1) is also introduced. The improved NRSR is formulated in Eq. (I.24). By applying Eq. (I.24), Eq. (I.23) is updated as follows.

$$X1_n^{IT} = x_n^{IT} - \left(randn \times \frac{(y_w - y_b) \times \Delta x}{2 \times (y_w + y_b - 2 \times x_n)} \right) + a \times (X_b - X_n^{IT}) + b \times (X_{r1}^{IT} - X_{r2}^{IT}) \quad (\text{Eq I.28})$$

In order to generate the new vector $x2_n^{IT}$, the location of the best vector X_b is updated with the position of the current vector x_n^{IT} in Eq. (I.28).

$$X2_n^{IT} = x_n^{IT} - \left(randn \times \frac{(y_w - y_b) \times \Delta x}{2 \times (y_w + y_b - 2 \times x_n)} \right) + a \times (X_b - X_n^{IT}) + b \times (X_{r1}^{IT} - X_{r2}^{IT}) \quad (\text{Eq I.29})$$

Finally,

$$x_n^{IT+1} = r_2 \times (r_2 \times X1_n^{IT} + (1 - r_2) \times X2_n^{IT}) + (1 - r_2) \times X3_n^{IT} \quad (\text{Eq I.30})$$

where

$$X3_n^{IT} = X_n^{IT} - \delta \times (X2_n^{IT} - X1_n^{IT}) \quad (\text{Eq I.31})$$

and r2 denotes a random number drawn from a uniform distribution on the unit interval (0,1). [20-24]

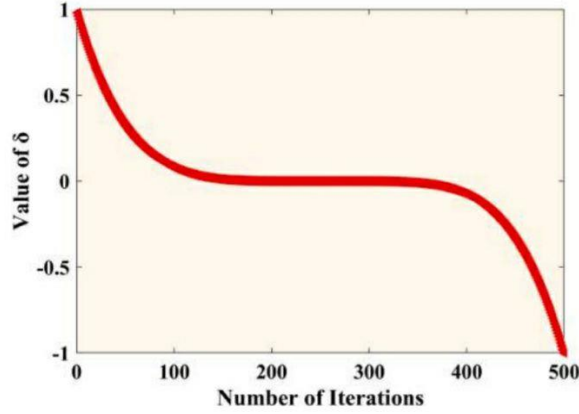


Figure.I 5. Variation of δ during the iterative process[1]

c: Trap Avoidance Operator (TAO)

To enhance the effectiveness of the proposed NRBO in tackling real-world problems, the TAO has been incorporated. The TAO is a modified and enhanced operator, adopted from. The TAO can significantly change the position of x_n^{IT+1} . By combining the best position X_b and the current vector position x_n^{IT} the TAO generates an enhanced solution, x_{TAO}^{IT} . The solution XIT TAO is produced if the value of rand is less than DF, as determined by Eq. (I.32).

$$\left\{ \begin{array}{l} X_{TAO}^{IT} = X_n^{IT+1} + \theta_1 \times (\mu_1 \times x_b - \mu_2 \times X_n^{IT}) + \theta_2 \times \delta \times (\mu_1 \times \text{Mean}(X^{IT}) - \mu_2 \times X_n^{IT}), \text{ if } \mu_1 < 0.5 \\ X_{TAO}^{IT} = x_b + \theta_1 \times (\mu_1 \times x_b - \mu_2 \times X_n^{IT}) + \theta_2 \times \delta \times (\mu_1 \times \text{Mean}(X^{IT}) - \mu_2 \times X_n^{IT}), \text{ Otherwise} \end{array} \right\}$$

(Eq I.32a)

$$X_n^{IT+1} = X_{TAO}^{IT} \quad (\text{Eq. I.32b})$$

The notation rand represents a uniform random variable between 0 and 1. The parameters θ_1 and θ_2 are uniform random variables within the ranges $(-1, 1)$ and $(-0.5, 0.5)$, respectively. The deciding factor, DF, is a critical component that influences the NRBO's performance.

The notation rand represents a random variable uniformly distributed between 0 and 1, and Δ denotes a scalar within the range $(0,1)$. μ_1 and μ_2 are random numbers generated as follows

$$\mu_1 = \beta \times 3 \times \text{rand} + (1 - \beta) \quad (\text{Eq I.33})$$

$$\mu_2 = \beta \times \text{rand} + (1 - \beta) \quad (\text{Eq I.34})$$

In this context, β represents a binary variable, either 1 or 0. The assignment of β is contingent upon the value of Δ , where β is set to 0 if Δ is greater than or equal to 0.5, and 1 otherwise.

The pseudocode for NRBO is provided in the Algorithm, and the flowchart of the proposed NRBO is depicted in Fig I. 6.

d: Computational Complexity

The computational complexity of initialization is $O(N)$, and the complexity of objective function evaluation and sorting is $O(N + N \cdot \log(N))$. The complexity of updating control parameters and solutions is $O(N \times D)$. Therefore, the overall computational complexity of NRBO is $O(N \times (1 + it \times N \times (1 + \log N + 2 \times N)))$, which is substantially less than the original Newton-Raphson method, with a complexity of $O(N \times N \times N)$. [25]

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

```

Initialization Phase:
1. Select the proper values of population size ( $N_p$ ) maximum number of iterations
   (  $Ma \times IT$ ), and the deciding factor (DF)
2. Initialize the initial random population position:
3. Assess the initial fitness value and the specify  $X_b$  and  $X_w$ 
Main Loop:
While( $IT < Max\_IT$ )

for  $n = 1:N_p$ 
    for  $j=1:dim$ 
        Choose randomly  $r_1 \neq r_2 \neq n$  between  $[1, N_p]$ 
        Determine the solution  $x_n^{IT+1}$  by Eq.30
    end for
    -%%% Trap Avoidance Operator (TAO) %%%
    if  $rand < DF$ 
        Find the solution  $X_{TAO}^{IT}$  by Eq. 28
         $X_n^{IT+1} = X_{TAO}^{IT}$ 
    else
        Determine the solution  $x_n^{IT+1}$  by Eq. 30
    end if
    Update  $X_b$  and  $X_w$ 
end for
 $IT=IT+1$ 
end while
Termination:
Return the best solution X, if termination criteria met
    
```

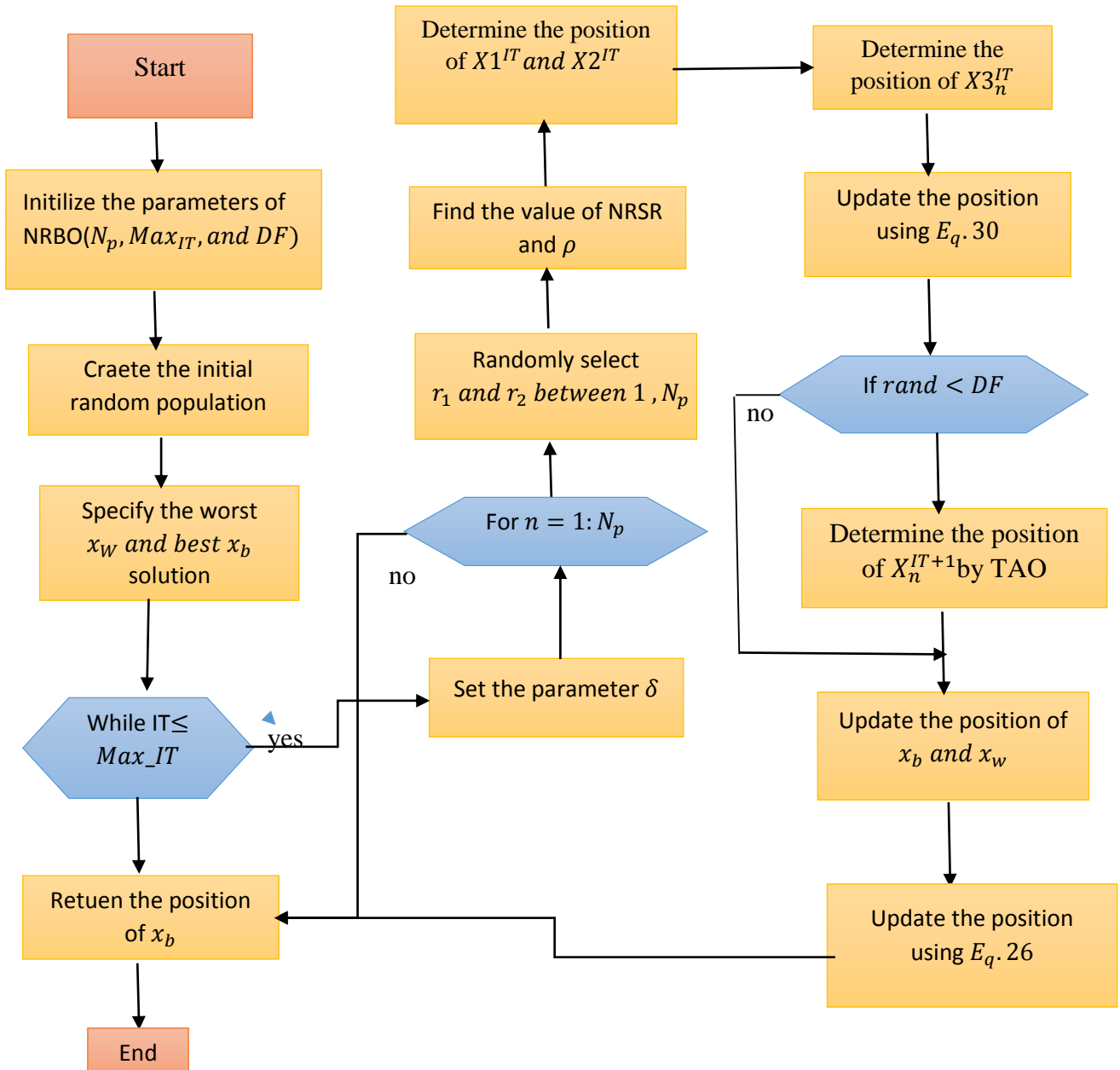


Figure.I.6. Followerchart of NRBO algorithm [1]

I.11.Conclusion

This chapter provided an in-depth exploration of optimization problems, thoroughly analyzing both exact and metaheuristic methods. While exact methods prioritize precision, they often encounter significant limitations when applied to complex problems due to their substantial computational requirements. In contrast, metaheuristic approaches offer a more adaptable and computationally efficient solution for addressing such challenges. The chapter has systematically

explained the core principles of metaheuristic algorithms, their classification, and their wide-ranging applications across diverse fields.

This chapter presented also the Newton-Raphson-Based Optimizer (NRBO) technique, detailing its algorithm and flowchart. This method will be utilized in the following chapter for applications in Mobile Ad hoc Networks (MANETs).

Chapter II: Mobile ad Hoc Networks (MANETs): concepts, protocols and challenges.

II.1. Introduction

II.2. Definition of Mobile Ad hoc Network

II.3. Type of Ad hoc Network

II.4. The Progress of MANET: (A Historical overview):

II.5. Types of MANETS

II.6. Topology

II.7. Characteristics

II.8. Application

II.9. Advantage of MANET

II.10. Challenges in MANET

II.11. Routing Protocols for MANET

II.12. Security

II.13. Conclusion

II.1. Introduction

In the field of computer networking, the term "network" refers to the underlying infrastructure that connects a group of devices together, facilitating communication and resource sharing among them. Networks can be classified into two main types: structured networks, which rely on fixed infrastructure such as routers and switches, and unstructured networks, as is the case with ad hoc networks. An ad hoc network is a specific type of network where devices establish connections without the need for pre-existing infrastructure. In these networks, devices form temporary connections to create a network spontaneously. This decentralized approach relies on the ability of devices to exchange information even in the absence of fixed infrastructure or when its use is impractical. Mobile Ad Hoc Networks (MANETs) are a notable type of ad hoc networks, characterized by the mobility of nodes and their ability to adapt to dynamic changes in the network.

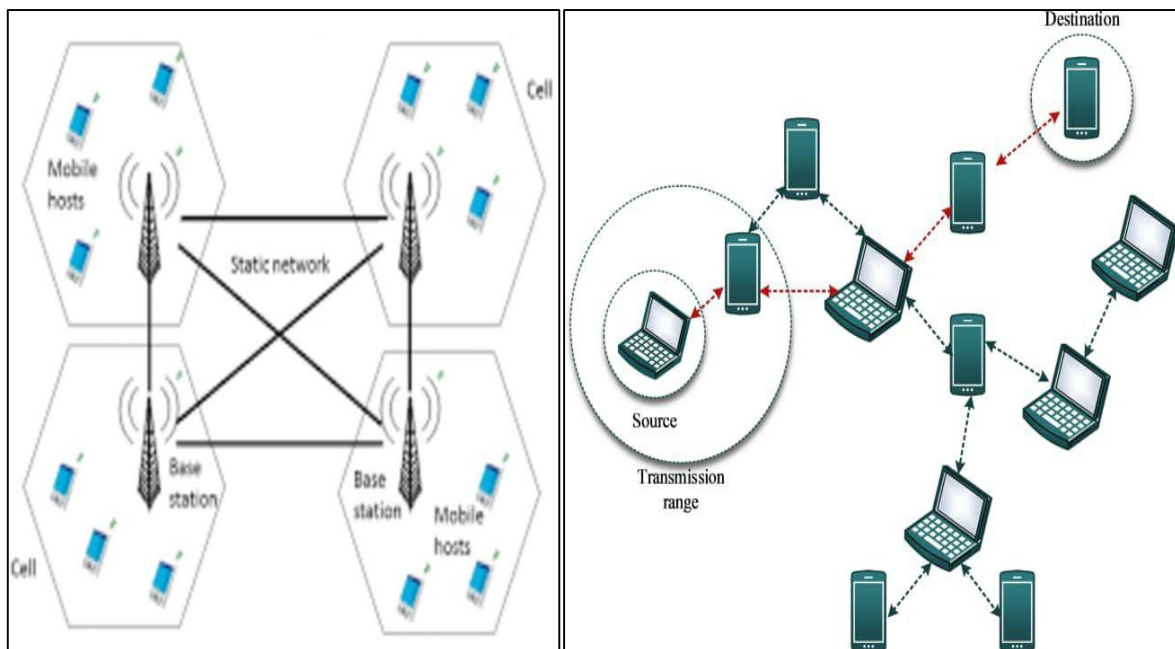
MANETs (Mobile Ad Hoc Networks) are defined by their mobile nodes that move independently and dynamically within the network. These nodes can enter or leave the network at any time, resulting in a continuously evolving network topology. This dynamic behavior introduces unique challenges for MANETs, including frequent disconnections, limited resources, and the necessity for efficient routing protocols.[26]

This chapter provides a comprehensive examination of ad hoc networks, with a particular focus on Mobile Ad Hoc Networks (MANETs). It delves into the fundamental principles, structural designs, and key characteristics of MANETs, as well as their practical applications, inherent challenges, and the strategies employed to address these challenges. Additionally, the chapter explores the diverse range of routing protocols utilized in ad hoc networks, offering a detailed analysis of proactive, reactive, and hybrid routing approaches. Through this extensive exploration, the chapter aims to equip readers with a deep understanding of the complex dynamics and potential advantages associated with ad hoc networks and MANETs.

II.2. Definition of Ad hoc Network

Wireless networks depend on centralized access points to facilitate communication, offering a stable and organized connectivity framework. On the other hand, ad hoc networks operate in a decentralized manner, forming spontaneous connections between devices without the need for centralized infrastructure. These networks are particularly suited for dynamic environments or situations where deploying traditional infrastructure is unfeasible, such as in

disaster recovery efforts or military operations. Ad hoc networks emphasize flexibility and adaptability, allowing devices to communicate directly and efficiently without relying on pre-established infrastructure. [27, 28]



A : wireless Network

B : Ad hoc Network

Figure.II.1: Comparison between Wireless Network and Ad hoc Network [29,30]

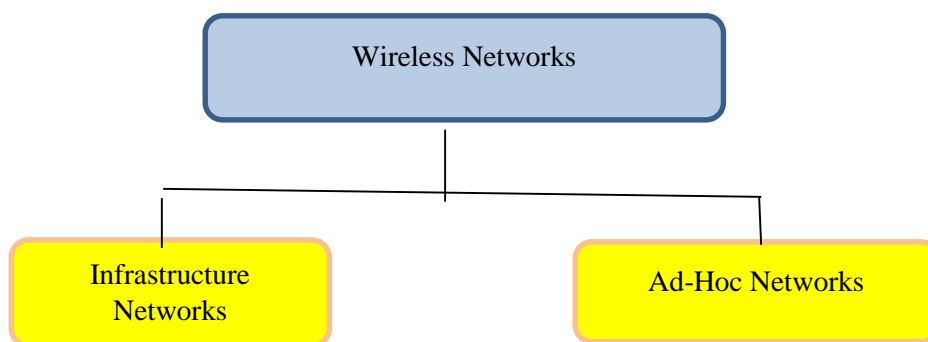


Figure.II.2. Wireless Networks Categories [31]

II.3. Type Ad hoc Network:

Ad hoc networks allow users to connect to the internet without requiring a dedicated router or wireless base station. These networks, commonly known as Local Area Networks (LANs), are temporary and can be set up quickly. Sometimes, ad hoc networks develop into

more structured wireless networks. Their primary goal is to enable communication between devices and individuals for a short period. Devices use their wireless network cards to establish direct connections, though these connections can be unstable. While multiple devices can connect at the same time, the network's performance might be limited. The term "ad hoc mode" refers to the spontaneous creation of such networks.[32 - 34]

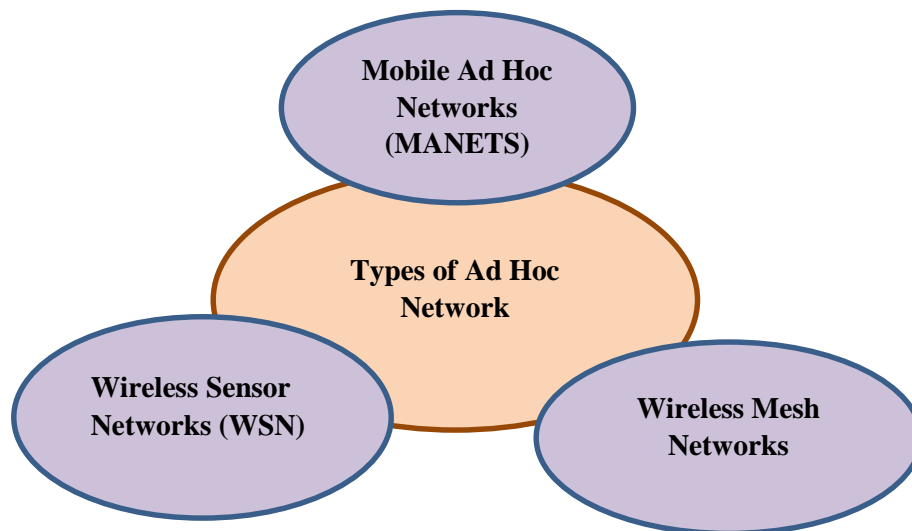


Figure.II.3: Type of ad hoc networks[35]

II.3.1. Mobile Ad hoc Networks (MANETs)

A Mobile Ad hoc Network (MANET) is a wireless network where mobile devices communicate without a fixed infrastructure. MANETs are built on a link-layer and wireless ad hoc network framework, enabling the creation of a highly adaptable and mobile network. As nodes move within the network, they form wireless connections to exchange data, collectively establishing a dynamic network structure. MANETs are characterized by their self-configuring and self-healing capabilities, which eliminate the need for pre-configuration. The network topology is fluid, allowing nodes to move freely and autonomously. These networks can be rapidly deployed and utilize mobile devices such as laptops, smartphones, tablets, and other

wireless devices for connectivity and communication. The main features of MANETs are depicted in Figure II.5.

In MANETs, when a node sends a message, it designates specific nodes as recipients. These networks can function either as standalone systems or as components of a larger internet infrastructure, providing flexibility for various use cases. By incorporating diverse transceivers between nodes, MANETs achieve a high level of dynamism and autonomy, ensuring efficient data flow and uninterrupted communication between devices. Each device in the network must possess the required information to sustain optimal performance.



Figure.II.4. Mobile Ad Hoc Network [31]

II.3.2. Wireless mesh network

Wireless mesh networks, also known as multi-hop wireless networks, consist of a set of interconnected wireless routers, creating a mesh-like infrastructure. Users can connect to these networks using devices such as laptops or smartphones with wireless capabilities, linking to the network through a router that acts as a wireless access point. This router then connects the network to a larger wireless network, which serves as the backbone for data transmission between users. These wireless mesh networks can communicate with one or more routers, providing connectivity to various networks, including the internet. These networks support a range of functions and are sometimes referred to as Wireless Ad Hoc Networks (WANETs).

Wireless Ad Hoc Networks (WANETs) are characterized by their ability to form networks dynamically and enable decentralized communication between devices without the need for fixed infrastructure. Devices in these networks can self-organize and establish direct connections, offering flexibility in deployment and supporting mobility. These networks are particularly useful in scenarios such as military operations, where soldiers can create a network on the battlefield to facilitate real-time communication and coordination. WANETs are also

valuable in emergency response situations, enabling rescue teams to communicate effectively and assist in search and rescue operations. Furthermore, WANETs are increasingly used in Internet of Things (IoT) applications, allowing devices to communicate directly and autonomously without the need for a centralized network infrastructure.

II.3.3. Wireless sensor networks (WSNs)

Wireless Sensor Networks (WSNs) operate without the need for fixed infrastructure, allowing users to monitor environmental conditions through wireless sensors. These networks are widely deployed in specific areas for the purpose of environmental management and monitoring. The base station of the network system is connected to the internet, enabling the sharing of collected data. The sensor nodes within the network communicate wirelessly, contributing to the formation of the wireless sensor network. The data gathered from the network helps users gain accurate insights into their environment, supporting informed decision-making.

Typically, network nodes are low-power devices, which presents challenges in implementing robust security measures due to their limited resources, such as memory and computational power. Potential risks include privacy breaches, manipulation of control systems, and disruption of network availability by attackers. This highlights the importance of securing encryption keys. A new routing method for wireless sensor networks has been proposed, considering energy consumption. The integration of wireless sensor networks is essential for the advancement of the Internet of Things (IoT), where security issues become increasingly important as the ecosystem expands.

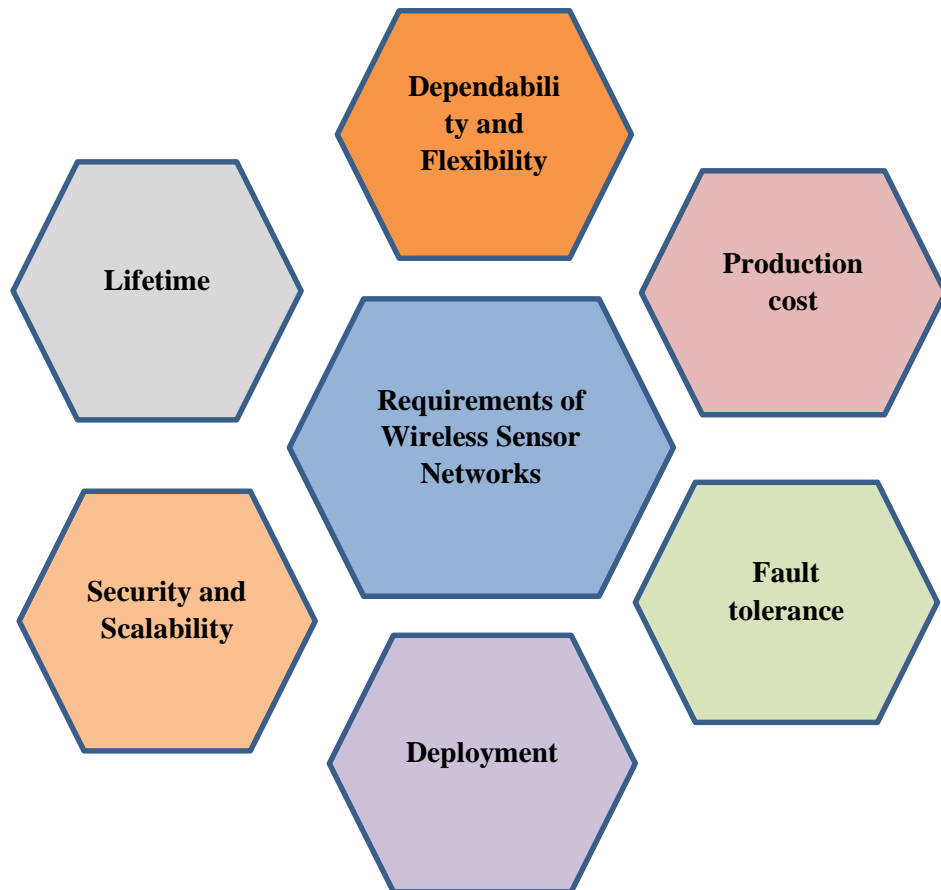


Figure.II.5. WSN Requirements [35]

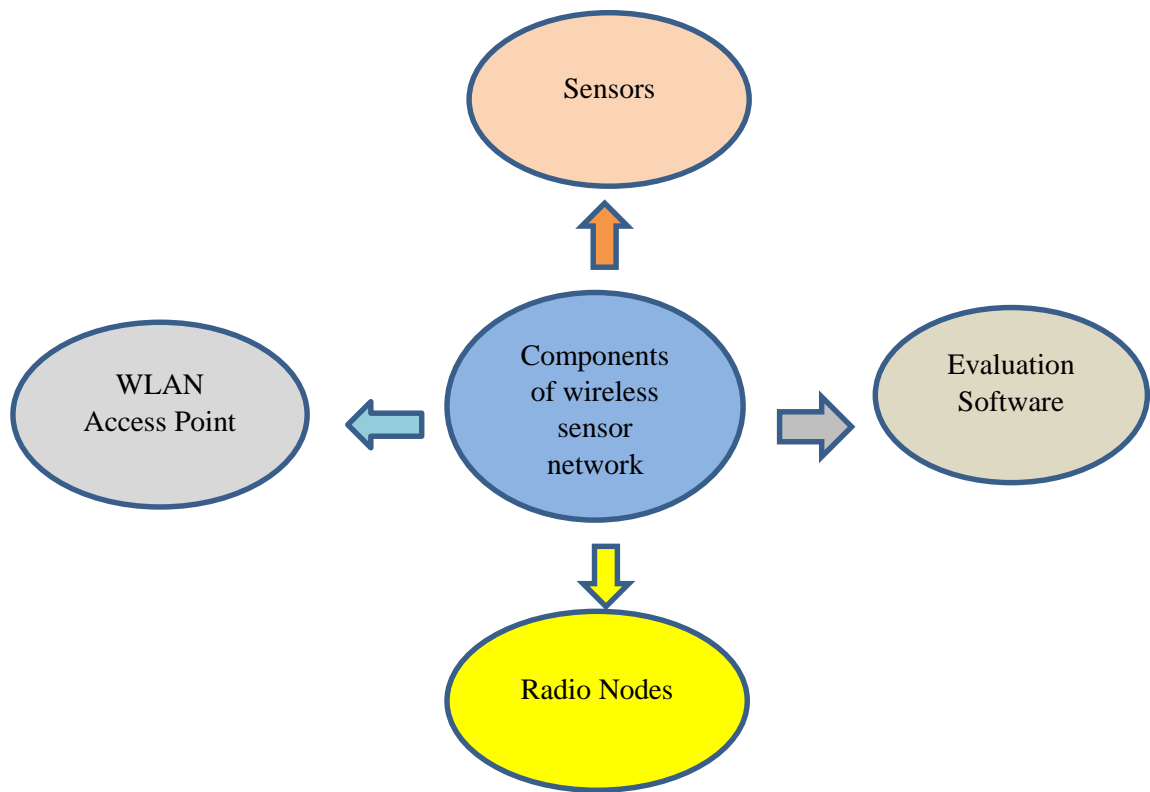


Figure.II.6: Components of Wireless sensor Network [35]

II.4. The Progress of MANET:(AHistorical overview) :

Mobile Ad Hoc Networks (MANETs) are a type of wireless network characterized by their lack of fixed infrastructure and their ability to self-organize dynamically. This makes them particularly well-suited for environments where traditional networking infrastructure is either unavailable or impractical to implement. The origins of MANETs date back to the 1970s, when they were primarily developed for military applications. The need for robust and adaptable communication systems in battlefield scenarios drove their early development. These networks were designed to ensure reliable communication for soldiers, capable of overcoming various physical and electronic obstacles encountered in the field.

During the 1980s and 1990s, the evolution of MANETs accelerated alongside progress in wireless communication technologies. The creation of more efficient and portable wireless

devices enabled researchers and developers to explore applications of MANETs beyond their initial military focus. This expansion included areas such as emergency response, disaster recovery, and even civilian recreational activities, where temporary networks could be quickly set up for specific events or needs. This period marked a significant shift, demonstrating the versatility and adaptability of MANETs in diverse scenarios.

The official efforts to standardize MANETs began in the late 1990s, with the IETF leading these initiatives and establishing a specialized working group for MANETs. This period saw numerous research and innovations aimed at addressing the complex challenges associated with these networks, such as routing, scalability, and security. As technology continued to evolve into the 21st century, MANETs found new applications in Internet of Things (IoT) devices and smart technologies, further strengthening their role in the future of wireless networking by providing flexible solutions for creating dynamic, self-configuring networks.[27]

II.5. Type of MANETS

Mobile ad-hoc networks (MANETs) are decentralized networks formed by mobile devices that establish communication through wireless links. As a device in a MANET moves, its connections with neighboring devices adapt dynamically. In these networks, each device operates as a router, responsible for relaying traffic intended for other nodes. To ensure effective traffic routing, every device in a MANET stores and updates the necessary routing data. MANETs can operate as independent networks or connect to the wider internet infrastructure.

Mobile Ad hoc Networks (MANETs) encompass various types, including Vehicular Ad hoc Networks (VANETs), which facilitate communication among vehicles to enhance intelligent transportation systems and enable cooperative driving. A specialized form of VANETs is the Infrastructure-less Vehicular Ad hoc Network (IVANET), where vehicles communicate directly without relying on fixed infrastructure, enabling peer-to-peer interactions and collaborative applications. Another variant of MANETs is the Smartphone Ad hoc Network (SPAN), which utilizes smartphones as network nodes to establish an ad hoc network. SPAN supports direct communication and resource sharing in situations where conventional network infrastructure is either inaccessible or unreliable.

* Mobile Ad Hoc Networks (MANETs) can be classified into two main types based on the number of hops required for communication between devices:

1. Single-Hop MANETs: In this type of network, devices communicate directly with each other within a single hop, meaning they are within the direct transmission range of one another. Examples of such networks include Bluetooth-based systems, where devices establish connections without the need for intermediate nodes.

2. Multi-Hop MANETs: In this type, devices are not always within direct communication range of each other. Instead, data packets are forwarded through intermediate nodes to reach the destination, requiring multiple hops. This type of network is more complex and is typically used in scenarios where devices are distributed over larger geographical areas.

Both types adhere to the fundamental principles of MANETs, such as self-configuration and dynamic topology adaptation, but they differ in terms of communication range and the routing mechanisms employed.[36,37]

II.5.1 Vehicular ad hoc network (VANET) :

Vehicular Ad Hoc Networks (VANETs) are dynamic networks composed of vehicles and communication elements, such as bridges, that form spontaneously during operation. These networks consist of a variety of vehicles and communication devices that interact wirelessly, facilitating the exchange of critical information. In VANETs, cars, phones, TVs, and other devices function as nodes within a small network. Various wireless technologies, including mobile phones, satellites, and WiMAX, enable seamless communication within these networks.

VANETs are rapidly evolving networks that primarily involve self-driving cars and face challenges due to their constantly changing topology caused by highly mobile nodes. The proliferation of vehicles equipped with computers and wireless communication devices further contributes to this evolution. VANETs provide inter-vehicle communication, significantly enhancing pedestrian safety and reducing accidents at blind intersections. They also play a pivotal role in traffic management during peak hours, potentially saving lives.

Although VANETs utilize specialized routing protocols, establishing reliable end-to-end paths remains a significant challenge. Effective collaboration among nodes is crucial, and the integration of mobile social networking into traditional VANET tools shows promising potential in enhancing participation. VANETs play a critical role in alleviating congestion and ensuring the safe passage of emergency vehicles.[38]

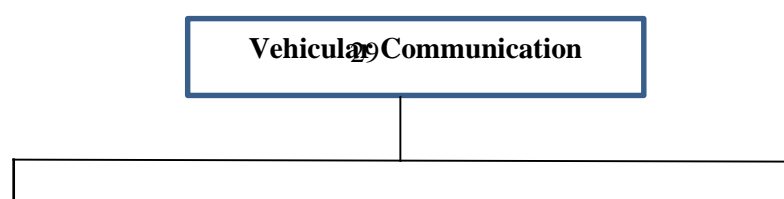


Figure.II.7: VANET Communication[41]

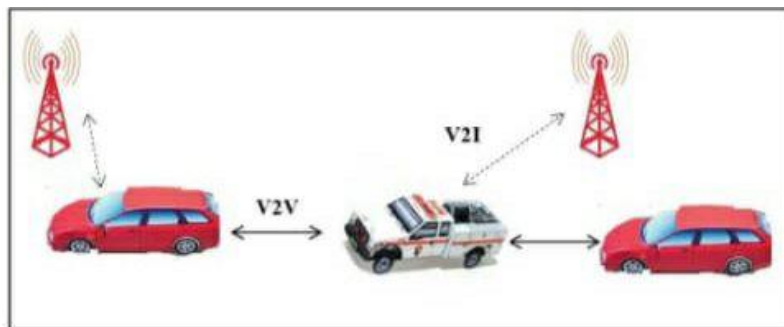


Figure.II.8: VANET Architecture [41]

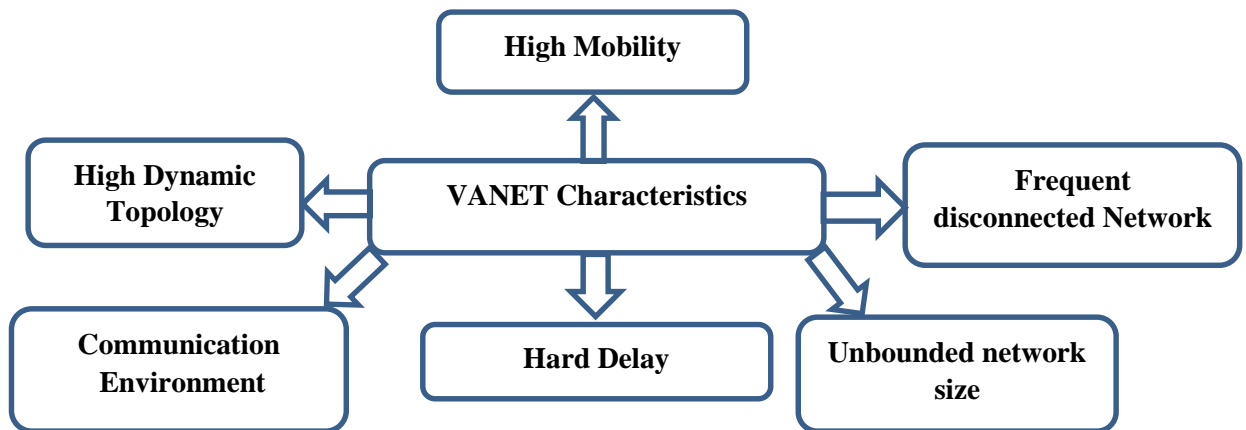


Figure II.9: Characteristics of VANET Network [41]

II.5.2. Intelligent vehicular ad hoc network:

Intelligent Vehicular Ad Hoc Networks (InVANETs) offer advanced functionalities, such as accessing vehicle-related data on digital maps and enabling optimized navigation. These networks are designed to complement mobile phones as the primary means of communication, rather than replace them. InVANETs utilize WiFi-based navigation systems to accurately determine vehicle locations in large-scale environments like universities, airports, or urban

areas. This capability helps users identify the most efficient routes with minimal traffic congestion. Additionally, InVANETs function as a digital city guide, assisting users in locating and exploring points of interest.

Intelligent Transportation Systems (ITS) involve communication between vehicles and between vehicles and roadside infrastructure, known as Roadside Units (RSUs). This vehicular communication enhances road safety, operational efficiency, and travel convenience by providing real-time information to drivers. Vehicle-to-Vehicle (V2V) and Vehicle-to-Roadside (V2R) communications serve different purposes: V2R is suitable for sparse networks and long-distance communication, while V2V enables direct interaction over short to medium distances, particularly in areas lacking roadside infrastructure. By facilitating seamless communication between vehicles and the surrounding infrastructure, ITS significantly improves safety and passenger comfort. To ensure uninterrupted internet connectivity for mobile devices, Mobile IPv6 is employed. Furthermore, solutions for implementing Mobile IPv6 in non-mobile networks have been developed, enabling consistent and seamless internet access.[39]

II.5.3. Smart phone ad hoc networks (SPANs)

Smartphone Ad Hoc Networks (SPANs) are a form of wireless ad hoc networks that leverage the built-in Wi-Fi capabilities of smartphones to enable direct peer-to-peer communication, eliminating the need for traditional network infrastructure. SPANs allow smartphones to dynamically form temporary networks, enabling communication in environments where cellular coverage or Wi-Fi access points are absent. In SPANs, smartphones autonomously connect with nearby devices, creating a decentralized network where each device acts as a node capable of forwarding data to others. Unlike conventional Wi-Fi networks, SPANs operate in ad hoc mode, allowing devices to communicate directly without relying on centralized access points. This flexibility makes SPANs particularly useful in emergency situations, disaster recovery efforts, or areas with limited connectivity. Furthermore, SPANs can enable innovative applications such as peer-to-peer file sharing, collaborative gaming, and location-based services, thereby enhancing the functionality and connectivity options of smartphones beyond standard network infrastructures.

For example, imagine a group of hikers in a remote area without cellular coverage or Wi-Fi access. Each hiker has a smartphone equipped with Wi-Fi capabilities. By enabling ad hoc mode on their smartphones, they can establish direct connections with one another, forming a SPAN. This network enables the hikers to communicate, share information, and coordinate

their activities without depending on external network infrastructure. The smartphones function as nodes within the network, relaying messages between devices as needed. This example demonstrates how SPANs can facilitate communication and collaboration in scenarios where traditional networks are unavailable or unreliable[40]

II.6. Topology

A Mobile Ad Hoc Network (MANET) is a network composed of mobile devices that are capable of self-organization, allowing them to operate independently without relying on fixed infrastructure. This network is characterized by a continuously changing configuration as the nodes move. Communication between nodes occurs either directly or through multiple intermediate nodes, creating a multi-hop network structure. The topology of a MANET depends on factors such as the movement patterns of the nodes, their transmission ranges, and the routing protocols used. Common topologies observed in MANETs include mesh, cluster, star, and hybrid configurations.[29,32]

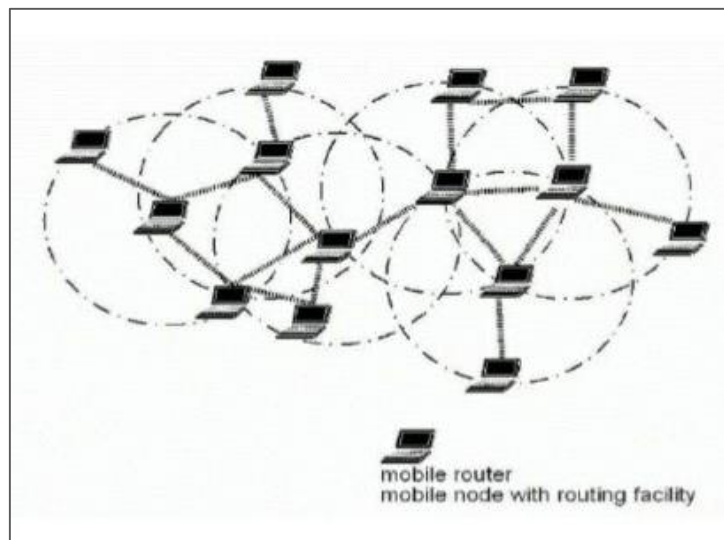


Figure II.10. Example Mobile Ad hoc Network[42]

Figure.II .11. illustrates a Mobile Ad hoc Network (MANET) scenario consisting of four mobile nodes: S, B, C, and D. In this setup, nodes S, B, and C are within each other's transmission ranges, allowing them to communicate directly and be considered neighbors. However, node D is located outside the transmission range of node S, making direct communication between them impossible. To enable communication between nodes S and D, an intermediary node, such as node C, is used as a router to forward data from S to D. This process, known as multi-hop routing, involves relaying data through multiple intermediate nodes along the path from the source (S) to the destination (D). add master thesis as reference



Figure II.11. Example for Mobile Ad hoc Networks [42]

The movement of nodes in a Mobile Ad Hoc Network (MANET) significantly influences the network's topology:

- **Frequent Link Instability:** Due to the continuous movement of nodes, they frequently enter and exit each other's transmission range. This results in repeated disruptions and reconnections, making it difficult to maintain stable and reliable links.
- **Route invalidation:** happens when node movements break the existing paths between them. In Mobile Ad Hoc Networks (MANETs), routing protocols need to constantly adjust by finding new routes or fixing broken ones. This continuous adaptation increases network overhead, leading to higher latency and more packet loss.
- **Network partitioning:** In extreme cases, when nodes move rapidly and far apart from each other, the network may split into isolated segments, leading to a disruption in communication between nodes in different segments. This phenomenon is known as (network partitioning).
- **Scalability Issues:** In Mobile Ad Hoc Networks (MANETs), as the number of nodes increases, the network dynamics become more complex, leading to more frequent route changes and higher network overhead. This can hinder the scalability of MANETs. [41,43]

II.7. Characteristics :

MANET (Mobile Ad-Hoc Network) has several key features that have led to its widespread use. For Ad-Hoc Routing protocols to be effective and reliable, the following characteristics are crucial :

- **Decentralized Operation:** In contrast to conventional networks that depend on a centralized management framework, Mobile Ad Hoc Networks (MANETs) function autonomously without

a fixed backbone infrastructure. In MANETs, control is decentralized, with each participating node sharing the responsibility for managing various network operations. Each node is capable of acting as a relay when necessary, performing essential functions such as routing and security enforcement. For the network to operate efficiently, nodes must cooperate and sustain uninterrupted communication with each other.

- **Multi-Hop Routing:** In scenarios where a node intends to send data to another node that is outside its immediate communication range, the data packet must be relayed through one or more intermediary nodes to successfully reach the intended destination.
- **Autonomous Nodes in MANETs:** In Mobile Ad Hoc Networks (MANETs), every mobile node operates autonomously and can serve as either a host or a router, facilitating decentralized communication without relying on a fixed infrastructure.
- **Dynamic Network Topology:** The mobility of nodes in MANETs leads to a network topology that may consist of both bidirectional and unidirectional links. This topology is highly dynamic, evolving rapidly and unpredictably as nodes move.
- **Lightweight Terminals:** Nodes in a MANET are typically mobile devices characterized by limited processing power, small battery capacity, and minimal memory resources.
- **Shared Communication Medium:** The wireless communication channel is accessible to any entity equipped with the appropriate technology and financial resources, making it challenging to enforce restrictions on channel access. [31,44]

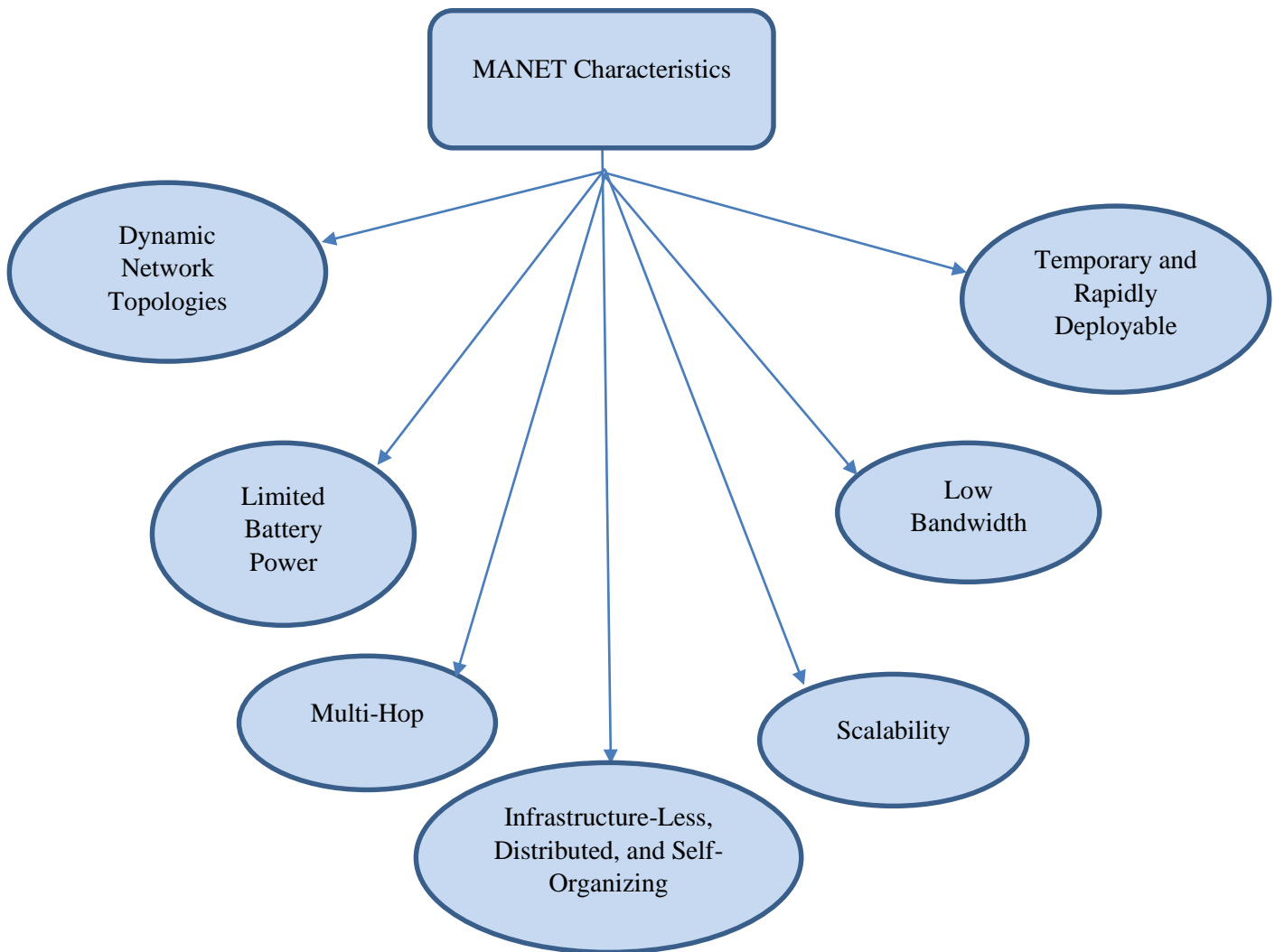


Figure II.12. Characteristics of MANET[41]

II.8. Application

Mobile Ad Hoc Networks (MANETs) have become increasingly popular due to their flexibility and adaptability, making them suitable for a wide range of real-world applications. Below are the primary areas where MANETs are utilized:

- *Military Applications* : MANETs are widely utilized in military operations due to their ability to provide a resilient and adaptable communication infrastructure, which is crucial for functioning in unpredictable and demanding environments.
- *Disaster Management* : In emergency situations, MANETs can be quickly set up to create provisional communication systems, enabling rescue teams to efficiently coordinate and exchange vital information.

- *Mobile Conferencing* : MANETs facilitate the creation of mobile conferencing solutions, enabling real-time communication and collaboration among users who are on the move, without relying on fixed infrastructure.
- *Personal Area Networks (PANs)* : MANETs can be employed to set up personal area networks, allowing for smooth data exchange and communication between devices that are in close proximity to each other.
- *Applications in Embedded Computing* : Integrating MANETs (Mobile Ad-Hoc Networks) into embedded computing systems allows for efficient information exchange and communication between devices and sensors, even in resource-limited environments.
- *Mobile Satellite Earth Stations* : MANETs provide the capability for mobile satellite earth stations to connect with one another, ensuring stable and reliable mobile communication in remote, isolated, or disaster-affected areas.
- *Mars Proximity Network (MPN)* : Mars Proximity Networks operate on a decentralized framework similar to Mobile Ad Hoc Networks (MANETs), where nearby nodes initiate communication without the need for pre-configuration. Participation in the network is formed by nodes within close range, necessitating protocols for neighbor discovery and dynamic route establishment. Additionally, these networks must support the exchange of external connectivity information, as some nodes may act as gateways to external networks, such as the Internet.
- *Inter-Planetary Area Networks (IPANs)* : Inter-Planetary Area Networks or IPANs represent sophisticated communication infrastructures engineered to establish connectivity across immense interstellar distances. These networks encounter substantial challenges, such as ensuring dependable data transmission, achieving minimal latency in service delivery, and sustaining uninterrupted end-to-end connectivity. To enable effective communication, IPANs leverage interplanetary spacecraft and Mobile Ad hoc Networks (MANETs), which facilitate data exchange among smaller spacecraft orbiting adjacent planets. IPANs are pivotal in planetary exploration, as they enable real-time data relay from a network of spacecraft to terrestrial ground stations, thereby enhancing our capacity to conduct scientific research and monitor remote celestial bodies.[45,46]

II.9. Advantage of MANET :

Mobile Ad Hoc Networks (MANETs) provide several significant advantages, which can be outlined as follows:

- *Decentralized Operation* : MANETs function independently without the need for centralized network control, allowing for autonomous operation.
- *Self-Configuring Capability* : Nodes within the network possess the ability to self-configure and also serve as routers, enabling dynamic network establishment.
- *Cost-Effectiveness* : MANETs are typically more economical to deploy than traditional wired networks.
- *Scalability* : The network can effortlessly expand to include additional nodes, making it highly scalable.
- *Enhanced Flexibility* : MANETs offer superior flexibility in terms of network deployment and adaptation.
- *Robustness* : The decentralized nature and absence of fixed infrastructure make MANETs highly resilient.
- *Rapid Deployment* : The network can be quickly and easily set up in any location without the need for extensive cabling.
- *Improved Reliability* : The presence of multiple communication paths increases the network's reliability.
- *Geographic Independence* : MANETs ensure access to information and services regardless of the user's geographic location.
- *Unrestricted Channel Access* : The network does not impose limitations on channel access, ensuring greater connectivity.

These characteristics make MANETs a versatile and efficient solution for a wide range of applications.[31]

II.10. Challenges in MANET :

Despite the many benefits offered by Mobile Ad Hoc Networks (MANETs), several critical challenges persist and remain unaddressed. In recent years, MANETs have emerged as a major area of research, with nearly every facet of these networks being investigated, often with varying levels of complexity. The following outlines the primary challenges associated with MANETs:

a: Limited Resources: Due to the scarcity of battery power, mobile nodes are forced to rely on it as their primary energy source. Both energy and storage capacities are severely limited.

b: Multiple Roles: Designing effective Medium Access Control (MAC) protocols that enhance spectrum reuse and, consequently, optimize overall channel utilization in Mobile Ad Hoc Networks (MANETs) remains a critical research challenge.

c: Dynamic Topology: The network allows for the dynamic addition or connection of nodes in diverse configurations, with nodes exhibiting mobility. The connections within the network change over time, primarily driven by the relative proximity between nodes.

d: Limited Bandwidth: The bandwidth capacity of wireless links is considerably lower than that of wired infrastructure networks. Additionally, the actual throughput of wireless communication is frequently much lower than the theoretical maximum transmission rate of a radio. This performance degradation is attributed to several factors, such as multiple access challenges, signal fading, noise, and interference conditions.

e: Heterogeneity: Heterogeneity is a fundamental characteristic of Heterogeneous Ad Hoc Networks (HANETs), which are increasingly pivotal in the Internet of Things (IoT) ecosystem. This trend is anticipated to continue shaping future research and practical implementations. In recent years, ad hoc networks have seen substantial expansion in their application across diverse fields, notably in intelligent transportation systems, smart city initiatives, military equipment management, and environmental surveillance.

f: Limited Survivability: A major challenge in deploying ad hoc networks lies in their inherent lack of resilience and heightened vulnerability to security threats. The reliance on wireless communication channels exposes these networks to various link-level attacks, such as message distortion, passive eavesdropping, and replay attacks. Moreover, the deployment of wireless ad hoc networks in dynamic and often adversarial environments; such as rapidly established military battlefield networks or remote sensor arrays for sensitive data collection, further amplifies their exposure to network security risks. These vulnerabilities can result in the compromise or failure of critical network components, thereby jeopardizing the overall integrity and functionality of the network.[42,47,48]

II.11. Routing Protocols for MANET

Routing protocols in Mobile Ad hoc Networks (MANETs) play a critical role in establishing and maintaining communication paths among nodes in a decentralized and highly

dynamic environment. These protocols enhance data transmission efficiency by identifying optimal routes based on the network's topology and the mobility patterns of its nodes. The selection of an appropriate routing protocol is influenced by various factors, including network size, scalability requirements, and the need for adaptability. Ad hoc routing protocols are broadly classified into three main categories: proactive, reactive, and hybrid. This classification reflects the fundamental strategies utilized in MANET routing. For further details, please consult Figure 2.9. [49]

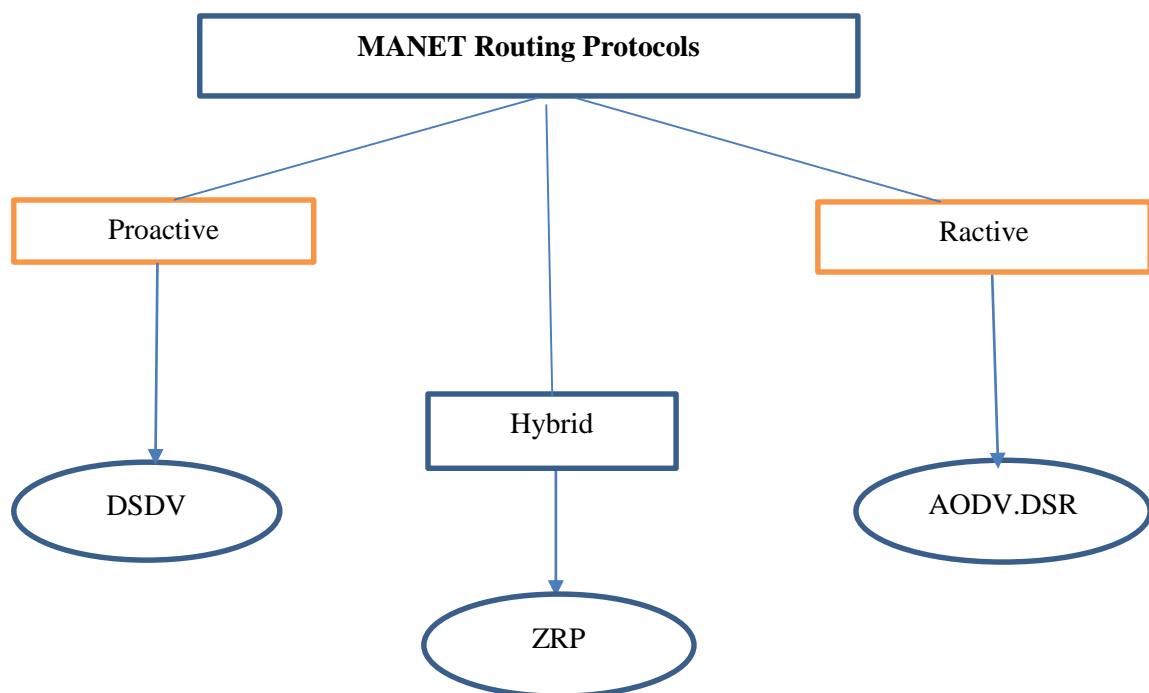


Figure II.13. Classification of MANET Routing Protocols[31]

II.11.1. Proactive routing protocol:

• **Definition:** Proactive routing protocols in Mobile Ad hoc Networks (MANETs) are designed to maintain up-to-date network topology information through a distributed mechanism. In this method, every node in the network is tasked with maintaining multiple routing tables, which are continuously updated and exchanged with neighboring nodes. This ongoing dissemination of routing information leads to a significant increase in network overhead. The operational principles of proactive routing protocols are akin to those employed in wired network routing protocols. Prominent examples of proactive routing protocols include Optimized Link State

Routing (OLSR), Destination Sequenced Distance Vector (DSDV), Fisheye State Routing, and Distance Vector.

Obstacle: In Mobile Ad Hoc Networks (MANETs), nodes share topology details by broadcasting messages across the network. While this process is crucial for maintaining network connectivity, it has a significant impact on network throughput and generates considerable traffic. The constant exchange of routing information leads to frequent updates in routing tables, consuming substantial bandwidth, energy, and memory resources. However, much of this routing information remains underutilized due to the transient nature of routes in such highly dynamic environments. Consequently, the continuous updating mechanism poses challenges for efficient resource utilization and overall network performance in MANETs.

• **Effectiveness:** effectiveness in a network is achieved by enabling nodes to continuously evaluate pre-defined routes and monitor any changes in the network topology. Since each node in the network has knowledge of the path to every other node, packets can be forwarded effectively and promptly without the need to wait for additional routing information, as the routes are already predetermined. To facilitate packet forwarding, each node maintains up-to-date routing information, which includes:

- 1: The number of hops required for packets to reach the destination node.
- 2: The most recent sequence number generated by the destination node.
- 3: The destination node's address.

While this approach is highly effective in small-scale networks, its efficiency diminishes in larger networks. In large-scale networks, it becomes increasingly difficult for each node to maintain and track the routing details of all other nodes, resulting in scalability challenges.

•**Examples:** In wireless networks, proactive routing protocols such as Destination-Sequenced Distance-Vector (DSDV), Global State Routing (GSR), Wireless Routing Protocol (WRP), and Optimized Link State Routing (OLSR) are widely utilized. These protocols are engineered to sustain current routing information through the regular exchange of control messages, thereby guaranteeing efficient and dependable data transmission throughout the network.

a: Destination-Sequenced Distance Vector (DSDV)

The goal of this routing protocol is to prevent loop formation by improving the Bellman-Ford algorithm. It employs the shortest path algorithm to determine the most efficient route to

the destination. To maintain network consistency, the protocol periodically broadcasts updated routing tables to all nodes in the network. However, a major drawback of this approach is the high network overhead caused by the frequent transmission of routing tables. As a result, this protocol is most suitable for small-scale networks and is not recommended for large networks with more than 200 nodes, as the significant bandwidth consumption required for regular updates becomes unfeasible.

b: Global state routing (GSR)

This routing protocol employs the link-state algorithm, where each node in the network generates and maintains a link-state table. This table is periodically shared with all adjacent nodes, leading to a notable reduction in the total number of control messages exchanged. However, the update packets tend to be large, and their size increases as the network grows, resulting in significant bandwidth consumption.

c: Optimized link state routing (OLSR)

The link-state algorithm serves as the foundation for this routing protocol, often known as the point-to-point routing protocol. In this protocol, link-state messages are periodically exchanged to maintain the consistency of routing information throughout the network. When a change in the network topology is detected, the update is broadcast exclusively to a designated subset of nodes. These nodes are then tasked with propagating the change further across the network. Nodes that receive the update process it but do not retransmit it to others. This method reduces the size of control messages and decreases the frequency of periodic transmissions, thereby improving overall network efficiency.

d: Wireless routing protocol (WRP)

Wireless Routing Protocol (WRP) is a table-based routing protocol that employs the Bellman-Ford algorithm to determine optimal routing paths. It bears similarities to the Destination-Sequenced Distance-Vector (DSDV) protocol and is specifically designed to ensure loop-free routing and rapid convergence in the event of link failures. WRP operates using four essential tables: the Distance Table (DT), Routing Table (RT), Link-Cost Table (LCT), and Message Retransmission List (MRL). These tables allow nodes to maintain accurate and updated information regarding their neighboring nodes, network topology, link costs, and pending message retransmissions. By maintaining consistent and current routing data, WRP

avoids routing loops through predecessor consistency checks and achieves faster network convergence during link failures.[50-52]

II.11.2.: Reactive routing protocol

- **Definition:** Reactive routing protocols in Mobile Ad hoc Networks (MANETs) differ from proactive protocols in that they do not preemptively maintain or disseminate complete network topology information to all nodes. Instead, these protocols initiate route discovery only when a node needs to transmit data to a specific destination. At that moment, the source node begins a process to locate the destination and determine the optimal route for data transmission. This on-demand strategy reduces network overhead but often results in longer delays in route establishment compared to proactive routing protocols.

In reactive protocols, routes are dynamically discovered and temporarily stored in a routing cache. These routes remain valid for a specific period and can be reused if the same destination is targeted again within that timeframe. Prominent examples of reactive routing protocols used in MANETs include the Temporally Ordered Routing Algorithm (TORA), Location-Aided Routing (LAR), Dynamic Source Routing (DSR), and Ad-hoc On-Demand Distance Vector Routing (AODV).

- **Obstacles:** The main drawback of reactive routing protocols is the delay incurred during the route discovery process, especially for communication over long distances. Unlike proactive routing protocols, reactive protocols are more energy-efficient and produce less network overhead. To avoid network congestion, when a source node does not have the necessary route information, it initially queries its neighboring nodes. If the required route information is not found, the search is extended to other nodes throughout the network. This approach effectively minimizes traffic by utilizing route maintenance mechanisms. However, during the route discovery phase, reactive routing protocols often lead to network-wide flooding, which can negatively affect overall network performance.

- **Effectiveness:** Efficiency: This routing technology significantly enhances bandwidth utilization by eliminating the need for continuous broadcasts. Reactive routing approaches are recognized for their bandwidth efficiency, as they activate route discovery processes only when required. As a result, reactive routing protocols are more widely implemented compared to proactive routing systems, largely because of their reduced bandwidth usage.

• **Examples:** Reactive routing protocols, also known as on-demand routing protocols, create routes only when necessary, minimizing overhead and dynamically adapting to changes in the network. Examples of such protocols include Ad hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR), Temporally Ordered Routing Algorithm (TORA), and Associativity-Based Routing (ABR). These protocols are specifically designed to optimize resource usage and maintain efficient communication in dynamic network environments.

a) Ad-hoc On-Demand Distance Vector (AODV): is a routing protocol specifically designed to minimize redundant transmissions in mobile ad hoc networks (MANETs). Its primary advantage lies in its ability to reduce control overhead by transmitting routing update packets only when necessary, rather than at regular intervals. This characteristic makes AODV highly effective in environments such as emergency response operations, military communications, and conference settings, where dynamic and efficient routing is essential.

In AODV, nodes that are not actively involved in communication paths do not generate routing updates or maintain current routing tables. This on-demand mechanism ensures that only nodes participating in active routes are responsible for maintaining routing information. As a result, nodes in a MANET utilizing AODV do not need to continuously monitor the cost to each destination unless they are actively communicating with other nodes. This approach significantly decreases network overhead and conserves resources, making AODV a highly efficient solution for dynamic and resource-limited environments.

b) Temporally ordered routing algorithm (TORA): The Temporally Ordered Routing Algorithm (TORA) is an evolution of the Lightweight Mobile Routing (LMR) protocol, retaining its fundamental routing mechanisms. One of the key strengths of TORA lies in its implementation of a lightweight adaptive multicast algorithm, which significantly improves its multicasting efficiency. However, a notable limitation of this protocol is its tendency to create temporary routes that may later become obsolete. Unlike other reactive routing protocols, TORA is uniquely optimized to function efficiently in highly dynamic and rapidly changing network environments.

c) Dynamic Source Routing (DSR): In the Dynamic Source Routing (DSR) protocol used in Mobile Ad Hoc Networks (MANETs), the process begins when the source node generates a Route Request (RREQ) packet. This packet includes details about both the source and destination nodes. The RREQ packet is then disseminated throughout the network via a flooding mechanism. As the packet traverses the network, each intermediate node that receives it adds

its own identifier to a list within the packet's header, since it lacks knowledge of the complete route to the destination. The packet is subsequently rebroadcast to neighboring nodes. If a node along the path fails to forward the data packet further, a Route Error (RERR) packet is created and transmitted back along the established route to inform other nodes of the routing failure.[53-55]

II.11.3. Hybrid Routing Protocol

- **Definition:** The hybrid routing protocol combines the advantages of both proactive and reactive routing strategies. The network is divided into zones, with each node acting as the center of its own zone. Nodes are categorized as either interior or peripheral based on their distance from the central node. This zonal architecture helps minimize network congestion and improves the efficiency of route discovery.

When the source and destination nodes are within the same zone, packets can be delivered quickly using the precomputed routing tables provided by proactive routing. On the other hand, if the source and destination nodes are in different zones, a delay might occur as reactive routing is employed to dynamically discover routes on-demand.

- **Effectiveness:** The Zone Routing Protocol (ZRP) improves network efficiency by restricting proactive routing to defined zones, thereby reducing the unnecessary spread of routing information. Within each zone, proactive routing ensures that nodes maintain current routing tables. For communication with nodes outside the local zone, reactive routing is used to establish routes as needed. This hybrid method significantly cuts down on the overhead of querying the entire network for route discovery, as routing information is already maintained within each zone through proactive routing. ZRP is designed to be flexible, with its performance depending on user behavior and the existing network setup.

- **Examples:** An example of a hybrid routing protocol is the Zone Routing Protocol (ZRP).

a) *Zone Routing Protocol(ZRP):* Zone Routing Protocol (ZRP) is a hybrid routing protocol that integrates the strengths of both proactive and reactive routing mechanisms. In ZRP, each node establishes a routing zone defined by a specific hop-count radius. Within this zone, the protocol operates in a proactive manner, maintaining and continuously updating routing information to ensure efficient communication within the zone. For destinations outside the node's routing zone, ZRP adopts a reactive approach, discovering routes on-demand, which helps minimize overhead and conserve resources. This dual-mode functionality enables ZRP

to scale efficiently: it behaves similarly to a proactive protocol in large networks with expansive routing zones, while acting reactively in smaller networks or when communicating with nodes outside the local zone. This flexibility makes ZRP well-suited for a variety of network environments.[56-58]

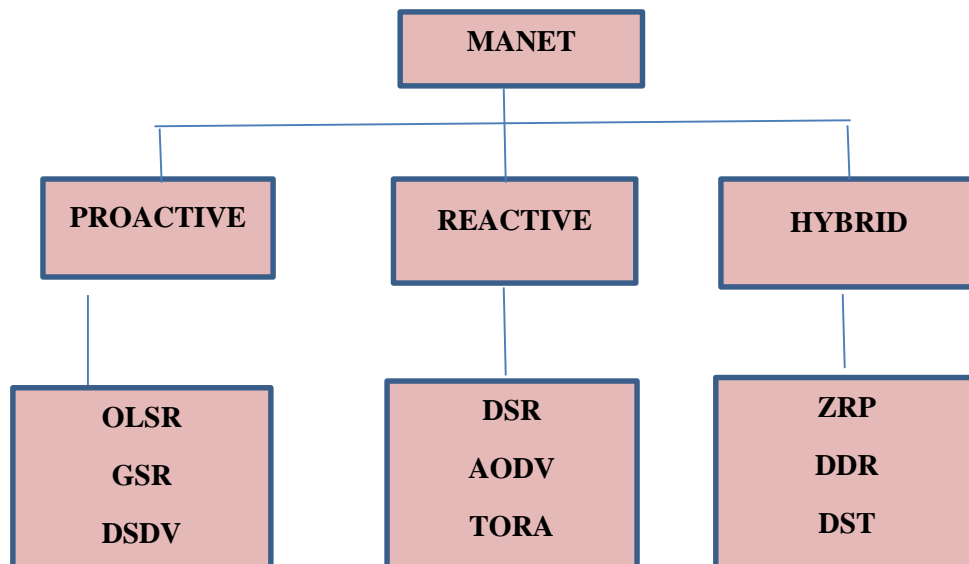


Figure II.14. Routing protocol for MANET [50]

II.12. Security

The main goal of a security service is to proactively enhance a network's defenses, making it more difficult for malicious nodes to compromise the network's security. However, the unique characteristics of Mobile Ad Hoc Networks (MANETs) pose significant challenges in effectively delivering these services. Striking a balance between these services is essential for maintaining robust security in MANETs. Prioritizing one service without considering its impact on others can lead to the failure of the overall security framework. Network applications play a vital role in mediating trade-offs among various security services. Nevertheless, implementing these services individually in a MANET while ensuring the reliability of each service remains a complex and challenging task. This discussion focuses on five key security services and the associated difficulties in providing them within the context of MANETs.

- *Availability:* For the service to function efficiently, it is essential that all network data and services are accessible to every authorized node. However, Mobile Ad Hoc Networks (MANETs) present significant challenges in maintaining availability due to their dynamic topology and open boundaries. Time is a critical factor in security, and the access time—defined as the duration required for a node to access network services or data—plays a crucial role. This aspect is often overlooked, as the multiple layers of security and authentication processes increase the time needed to navigate through these security levels, thereby negatively impacting overall accessibility.

- *Authentication:* The main objective of this service is to establish secure and reliable communication between two distinct nodes. When a node receives data packets from a source, it is essential to verify the identity of the originating node to ensure its authenticity. However, key distribution and key management present considerable challenges. To tackle these issues, digital certificates are utilized as a mechanism to deliver this authentication service.

- *Data Confidentiality:* In a network, each node should only be able to access the services for which it has explicit authorization. Although encryption is widely employed to maintain data confidentiality in most systems, the decentralized structure of MANETs (Mobile Ad Hoc Networks) introduces significant challenges in key distribution. Traditional key management approaches often become difficult to implement or may prove impractical in such environments due to the lack of a centralized authority.

- *Integrity:* Integrity security services are designed to guarantee that only authorized nodes have the ability to create, modify, or delete data packets. A Man-in-the-Middle (MITM) attack directly targets this service by intercepting the packets and then altering or deleting them. This results in a breach of data integrity, as the original information is compromised by the unauthorized changes made by the attacker.

- *Non-Repudiation:* guarantees that both the sender and the receiver cannot deny the validity of their data or actions within the service. Specifically, this means that Node 1 cannot deny sending a packet to Node 2 once Node 2 has received and acknowledged it.[59,60]

* **Table1:** shows the reactive routing protocols (Routing protocol class, Routing structure, Multiple Routes, Route Metric Method and Route maintenance and Advantage / Disadvantage).

Table II.1: Reactive routing protocols[50]

Protocol	Routing protocol class	Routing structure	Multiple routes	Route metric method	Route Maintenance	Advantage / Disadvantage
Ad hoc on _ demand distance vector(AODV)	Reactive routing protocol	Flat	No	Freshest and shortest path	Route table	Adaptable to highly dynamic topologies/scalability problems , large delay, hello messages
Dynamic source routing (DSR)	Reactive routing protocol	Flat	Yes	Shortest path , or next available in route cache	Route cache	Mutiple routes , promiscuouys overhearing/scalability problems due to source routing and flooding , large delays
Temporally ordered routing algorithm(TORA)	Reactive routing protocol	Flat	Yes	Shortest path , or next available	Route table	Multiple routes / temporary routing loops

* **Table2:** shows the hybrid routing protocols (Routing protocol class, Routing structure, Multiple Routes, Route Metric Method and Route maintenance and Advantage / Disadvantage).

Table II.2: Hybrid routing protocols[50]

Protocol	Routing protocol class	Routing structure	Multiple routes	Route metric method	Route Maintenance	Advantage /Disadvantage
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Zone routing protocol (ZRP)	Hybrid routing protocol	Flat	No	Shortest path	Intrazone and interzone tables	Reduce retransmission / overlapping zones
Distributed spanning trees based routing protocol (DST)	Hybrid routing protocol	Hierarchical	Yes, if available	Forwarding using the tree neighbors and the bridges using shifting	Route tables	Reduce retransmission / root node
Distributed dynamic routing (DDR)	Hybrid routing protocol	Hierarchical	Yes, if alternate gateway nodes are available	Stable routing	Intrazone and interzone table	No zone map or zone coordinator / preferred neighbours may become bottlenecks

* **Table3:** shows the comparison of three routing protocols (Proactive, Reactive, and Hybrid).

Table II.3: Comparison of routing protocols [50]

Parameters	Proactive	Reactive	Hybrid
Storage requirement	Higher	Dependent on no of routes maintained or needed	Depends on size of each zone or cluster
Routing schema	On demand	Table driven	Combination of both
Mobility support	Route maintenance	Periodical updates	Combination of both
Routing overhead	Low	High	Medium
Routing informatin	Keep stored in table	Doesn't store	Depends on requirement

Storage capacity	Low generally	High , due to the routing tables	Depens on the size of zone
Routing philosophy	Mosty flat	Flat	Hierarchical
Delay	Low	High	Low for local destinations and high for inter_zone

II.13. Conclusion

In summary, Mobile Ad hoc Networks (MANETs) present a decentralized and highly adaptable solution for dynamic communication environments. Their flexible topologies, including mesh, cluster, and hybrid structures, ensure both adaptability and robustness. Nonetheless, security vulnerabilities persist as a significant concern due to the open and dynamic nature of these networks.

Routing protocols such as OLSR, AODV, and ZRP play a critical role in enabling efficient data transmission by balancing proactive, reactive, and hybrid strategies. However, the dynamic movement of nodes continues to pose challenges for routing protocols, impacting their performance and reliability. In the next chapter, we will explore the evaluation and application of the NRBO (Newton-Raphson-Based Optimization) method to enhance routing optimization in MANETs.

Chapter III. Evaluation and application of NRBO method in Manet routing optimization

III.1. Introduction

III.2. Part 1: Evaluation

III.3. Part 2: Application

III.4. Simulation Results

III.5. Conclusion

III.1. Introduction

Efficient routing protocols are a critical component in Mobile Ad hoc Networks (MANETs) to ensure reliable communication between nodes. These networks are decentralized and self-organizing, consisting of mobile devices without fixed infrastructure, making robust routing mechanisms essential for establishing sustainable communication paths. Traditional routing protocols face significant challenges in such dynamic environments, including high route discovery overhead, network congestion, and difficulties in managing constantly changing topologies.

The high mobility of nodes and resource constraints in MANETs lead to frequent route rediscovery and instability in maintaining active routes. Additionally, limited bandwidth and competition among multiple nodes for network resources exacerbate congestion, reducing communication efficiency. The dynamic nature of these networks, where nodes continuously join and leave, further complicates topology management.

To address these challenges, adaptive and efficient routing strategies are needed capable of dynamically responding to changing network conditions while optimizing route management. Advanced routing protocols can enhance communication performance, reduce overhead, and ensure reliable connectivity in MANETs.

This chapter presents an innovative routing approach for MANETs based on the Newton-Raphson-Based Optimizer (NRBO) algorithm. Extensive simulations using MATLAB were conducted to evaluate its effectiveness. The chapter is divided into two main sections: part one evaluation of NRBO method through different test functions and part 2 application of NRBO in MANETs routing.

III.2. Part 1: Evaluation

III.2.1. Test Functions

To ensure the validity of any novel metaheuristic algorithm, it must be rigorously evaluated using benchmark test functions with known global optima, under a fixed number of iterations to enable fair comparisons with existing methods. In this thesis, the considered metaheuristic is assessed using the standardized set of 23 test functions introduced in the 2005 IEEE Congress on Evolutionary Computation (CEC'05).

The test functions are categorized into three distinct groups:

a: The Function F01-F07 high-dimensional unimodal functions feature a single global optimum and are specifically designed to evaluate metaheuristics' exploitation performance (see Fig. III.1).

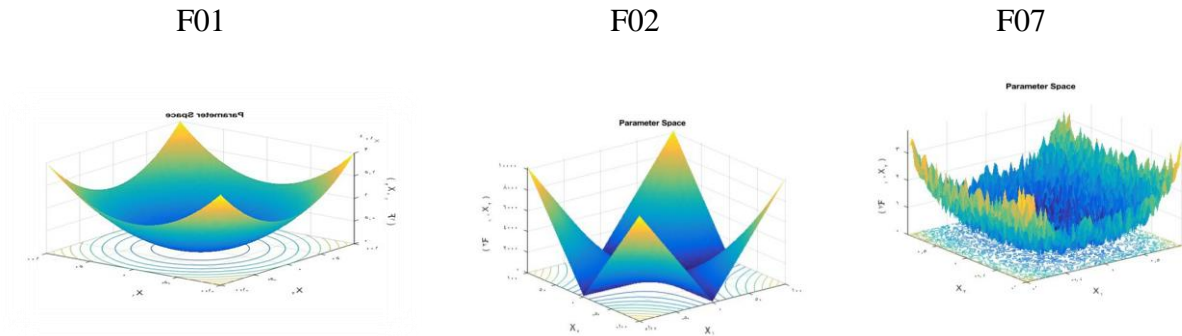


Fig. III.1. Example on High-Dimensional Unimodal Functions F1, F2, F7

b: High-dimensional multimodal functions (F08-F13) represent the most complex optimization problems due to the presence of numerous local optima. To solve them efficiently and avoid premature convergence, it is crucial to have an exceptionally high exploration capability (see Figure III.2)

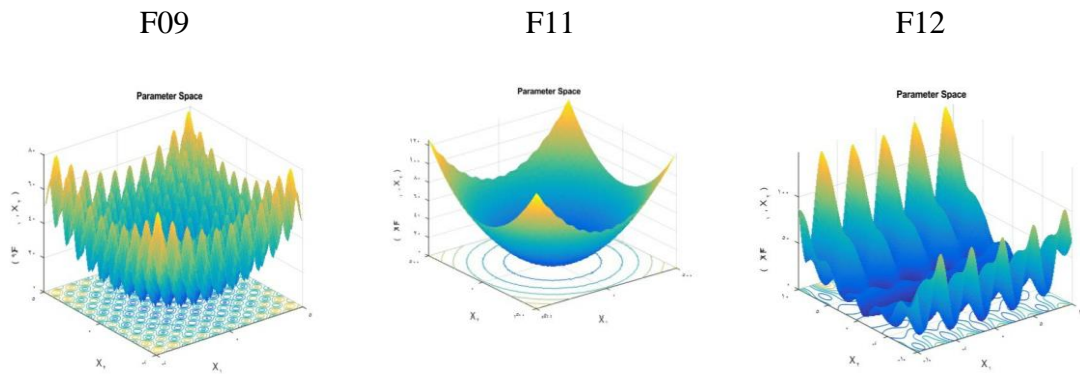


Figure III.2. Example of High-Dimensional Multi-modal Functions: F9, F11, F12

c: The low-dimensional multimodal functions (F14-F23): These share characteristics with the earlier category, but due to their reduced dimensionality, they contain fewer local optima (as illustrated in Figure III.3).

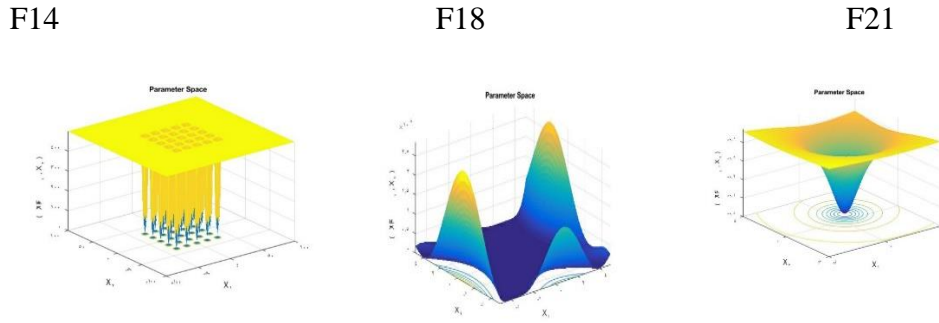


Figure III.3. Example of Low-Dimensional Multi-modal Functions: F14, F18, F21.

This table summarizes a suite of standard benchmark test function frequently employed to analyze the effectiveness of optimization algorithms. Characterized by distinct features such as multiple local optima, non-linearity, and convexity, these functions serve as robust tools for testing an algorithm’s precision and robustness in identifying global optima across different landscapes. Each entry includes the function name, dimension (D), search space bounds, and the theoretical optimum value.

Table III.1: Test Functions

Test functions		D	Range	Optimum
1	$f_{01} = \sum_{i=1}^n x_i^2$	30	[-100,+100]	0
2	$f_{02} = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i$	30	[-10,+10]	0
7	$f_{07} = \sum_{i=1}^D ix + random[0,1]$	30	[-1.28,+1.28]	0
9	$f_{09} = \sum_{i=1}^D [x_i^2 - 10 \cos(2\pi x_i) + 10]$	30	[-5.12,+5.12]	0
11	$f_{11} = \frac{1}{4000} \sum_{i=1}^D x_i^2 - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	30	[-600,+600]	0
12		30	[-50,+50]	1.5705

	$f_{12} = \frac{\pi}{D} \left\{ 10 \text{SIN}^2(\pi y_i) + \sum_{i=1}^{D-1} (y_i - 1)^2 [1 + 10 \text{SIN}^2(\pi y_i + 1)] + (yD - 1)^2 + \sum_{i=1}^D u(x_i, 10, 100, 4) \right\}$ $y_i = 1 + \frac{x_i + 1}{4}, u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i > a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$			
14	$f_{14} = \left[\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{j-1}^2 (x_i - a_{ij})^6} \right]^{-1}$	2	[-65.53,+64.53]	0.998004
18	$f_{18} = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)] \times [30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	4	[-5,+5]	0.0003075
21	$f_{21} = - \sum_{i=1}^5 [(x - a_i)(x - a_i)^T + C_j]^{-1}$	4	[0,+10]	-10.1532

III.2.2. Optimization results

The following tables summarize the results obtained for different test functions, showing the mean over 25 executions and the corresponding standard deviation

Table III.2: Optimization results for high-dimensional unimodal functions F1, F2, and F7

Functions	F1	F2	F7
Mean	2.85495 e-315	7.96077 e-307	3.03168 e-05
Std	0	0	2.33466 e-05

Table III.3: Optimization results for high-dimensional multimodal functions F9, F11, and F12.

Function	F9	F11	F12
Mean	2.27373 e-15	0	0.12401
Std	1.13686 e-14	0	0.05654

Table III.4: Optimization results for low-dimensional multimodal functions F14, F18, and F21.

Function	F14	F18	F21
Mean	1.31546	2.99999	-9.70168
Std	0.74238	2.28608 e-15	1.41290

III.2.3. Observations

a) Mean (Average Value)

high-dimensional unimodal functions	<p>For F1 and F2 , the mean values are negligibly small (approaching zero), indicating minimal functional output.</p> <p>F7 exhibits a slightly higher mean ($\sim 3.03 \times 10^{-5}$), though still very small.</p>
High-dimensional multimodal functions	<p>F9 exhibits an extremely small mean, approximately zero ($\sim 2.27 \times 10^{-15}$).</p> <p>F11 has a mean of zero, indicating that all its values are precisely zero.</p> <p>The F12 test function yielded a mean value of about 0.124, demonstrating its proximity to the optimal value of 1.5705.</p>
The low-dimensional multimodal functions	<p>For F14, a mean value of 1.315446 was obtained, which is close to its optimal value of 0.9980.</p> <p>Similarly, F18 yielded a mean value of 2.9999, approaching its optimum of 0.0003075.</p> <p>Finally, F21 displayed a mean value of -9.70168, demonstrating its proximity to the optimal value of -10.1532.</p>

Standard Deviation (Variability)

high-dimensional unimodal functions	<ul style="list-style-type: none"> • F1 and F2 show a standard deviation of zero confirming absolute consistency in results (no variation). • F7 has a low standard deviation ($\sim 2.33 \times 10^{-5}$), reflecting highly concentrated values with minimal dispersion.
High-dimensional multimodal functions	<ul style="list-style-type: none"> • F9 shows minimal dispersion ($\sim 1.13 \times 10^{-14}$), reflecting near-constant values. • F11 has zero standard deviation, confirming absolute uniformity (no variation). • F12 demonstrates measurable variability (Std ~ 0.0565), indicating a moderate spread in its results.
The low-dimensional multimodal functions	<ul style="list-style-type: none"> • F14 displays a moderate standard deviation (~ 0.74), suggesting moderate variability in its results. • F18 has an extremely low standard deviation ($\sim 2.28 \times 10^{-15}$), implying near-identical results with almost no dispersion. • F21 demonstrates a higher standard deviation (~ 1.41), indicating greater variability in its results compared to the other functions.

Discussion of Test Function Results

The analysis of the mean values and standard deviations across various high-dimensional unimodal, high-dimensional multimodal, and low-dimensional multimodal functions reveals interesting insights into their characteristics and the consistency of observed results.

For Mean Values: For functions F1, F2, F7, F9 and F11 consistently show negligibly small mean values, nearly approaching to the optimum value zero. For functions F12, F14, F18 and F21, the algorithm yields optimization results so close to its optimal value.

The standard deviation provides crucial information about the variability of results. For almost all functions the NRBO method reveals a very low standard deviation, implying highly concentrated and consistent values and demonstrating its stability.

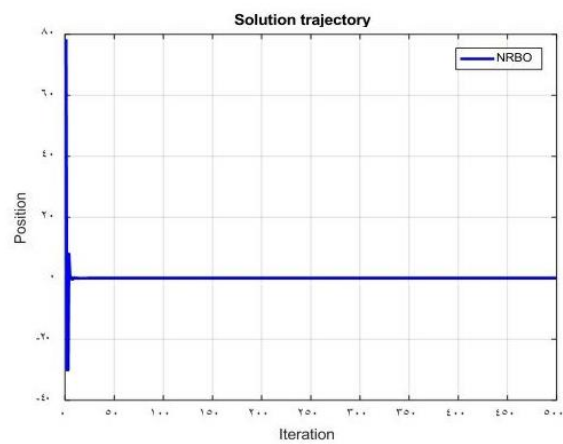
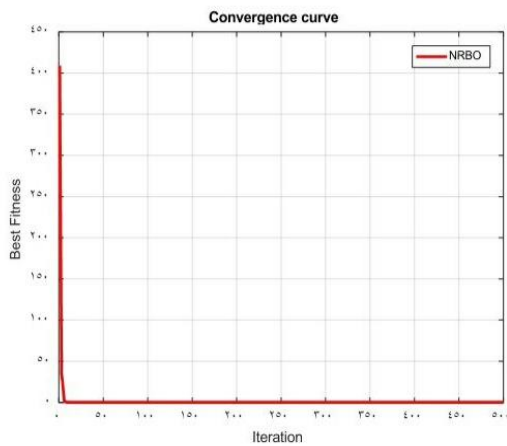
III.2.4. Curves

✓ *Convergence Curve:*

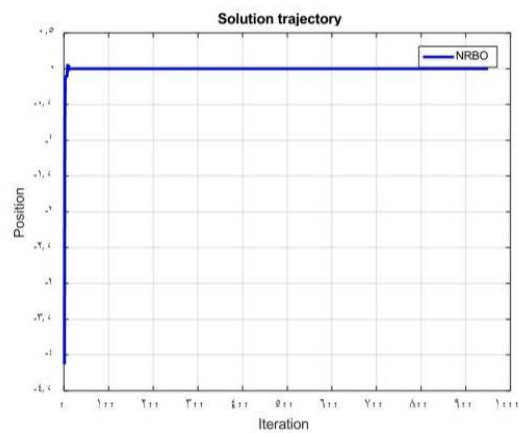
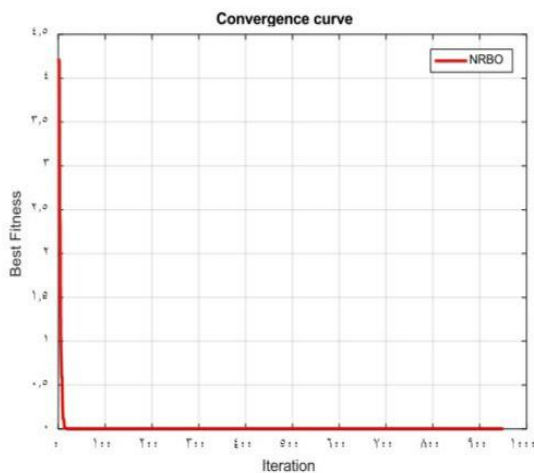
The convergence curve tracks the improvement in the best fitness value across iterations. At the start, the fitness value is notably high, but it drops sharply and rapidly in the initial iterations.

✓ *Solution Trajectory:*

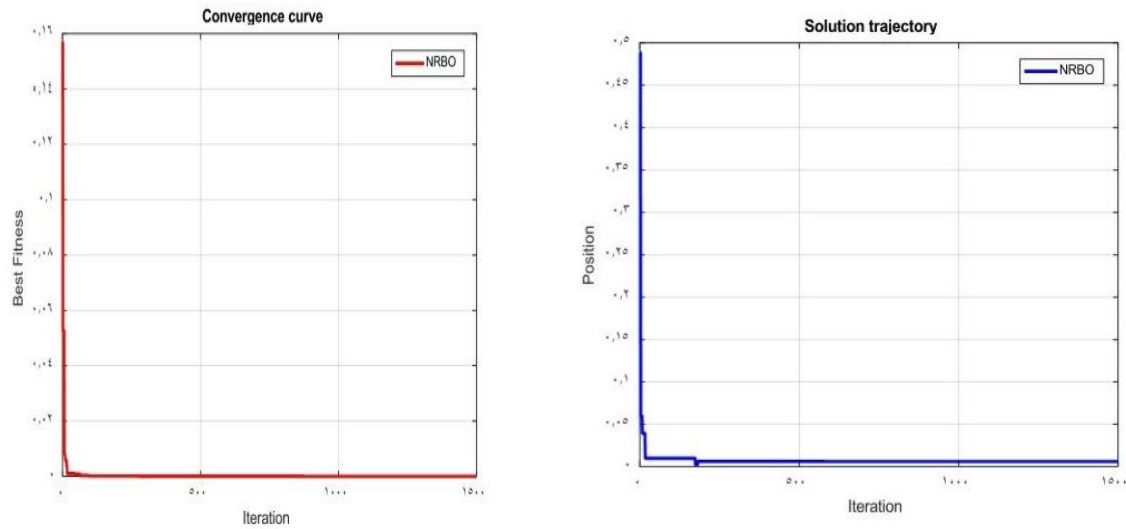
The solution trajectory shows how the candidate solution's position evolves during optimization. Early on, the trajectory displays significant fluctuations, reflecting active exploration. However, it quickly stabilizes as iterations progress, with little to no further positional changes observed.



F01



F02

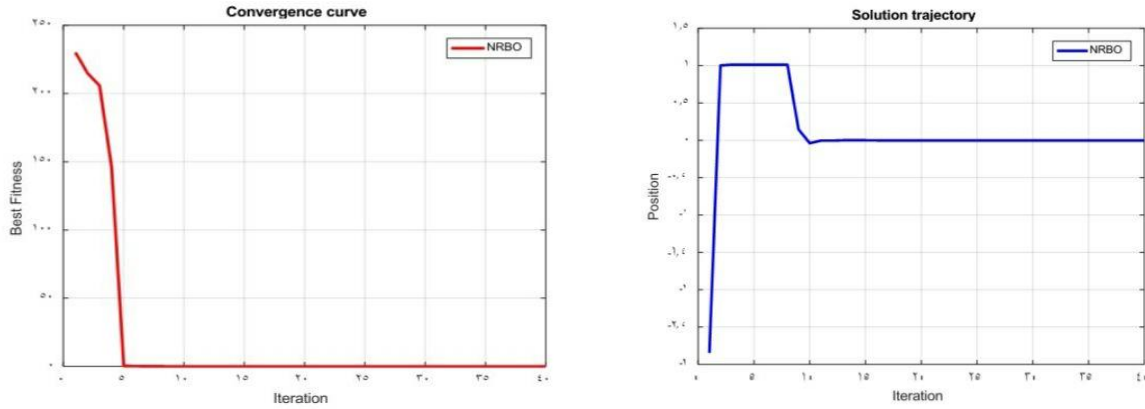


F07

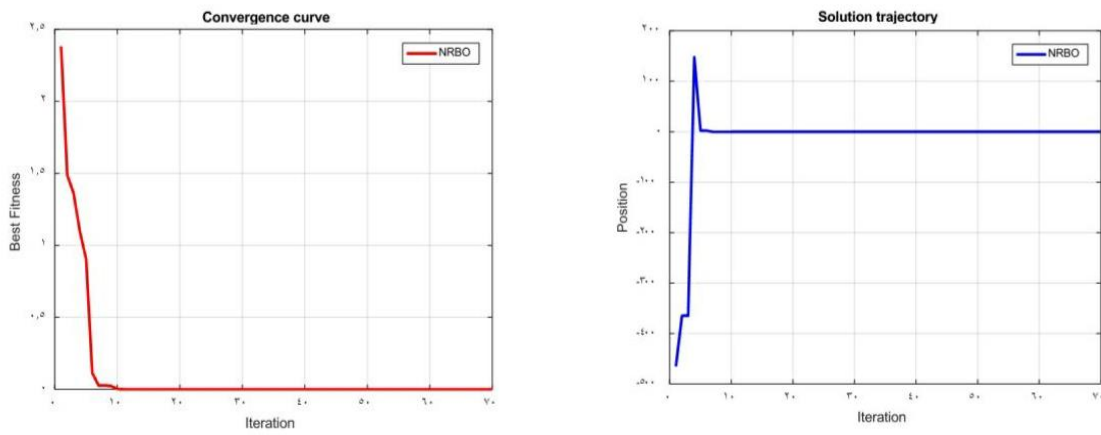
Figure III.4. Convergence Curve and Solution Trajectory for High-Dimensional Uni-modal Functions F1, F2, F7

✓ Observations:

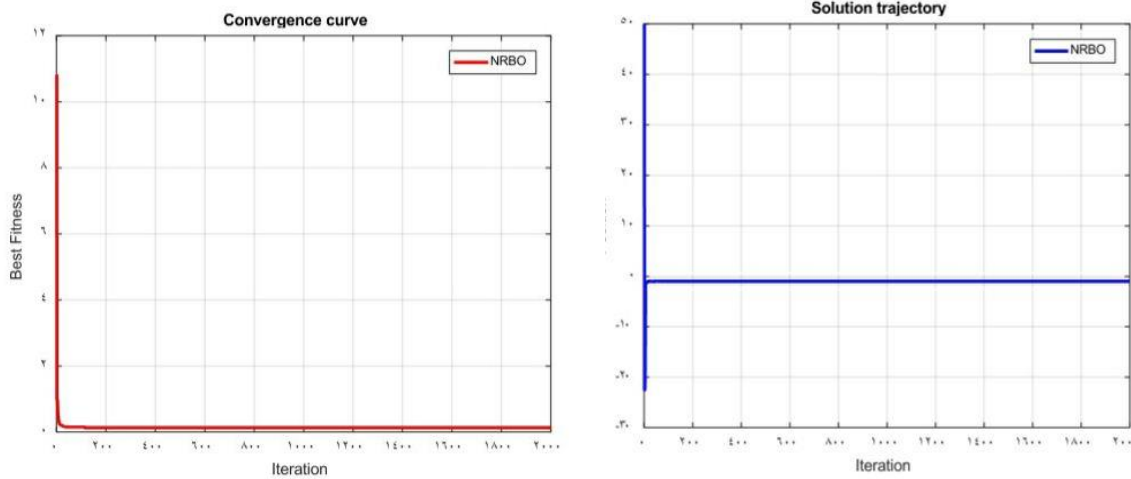
- The steep decline in the convergence curve highlights the NRBO algorithm's efficiency in finding high-quality solutions early in the optimization process.
- The early stabilization in both the convergence curve and solution trajectory suggests:
 - Strong initial exploration and exploitation capabilities.
 - A possible risk of premature convergence to a local optimum unless global optimality is confirmed.
- The absence of significant improvement after the 10th iteration indicates that incorporating additional diversification mechanisms could help prevent stagnation and encourage further exploration when needed.



F9



F11

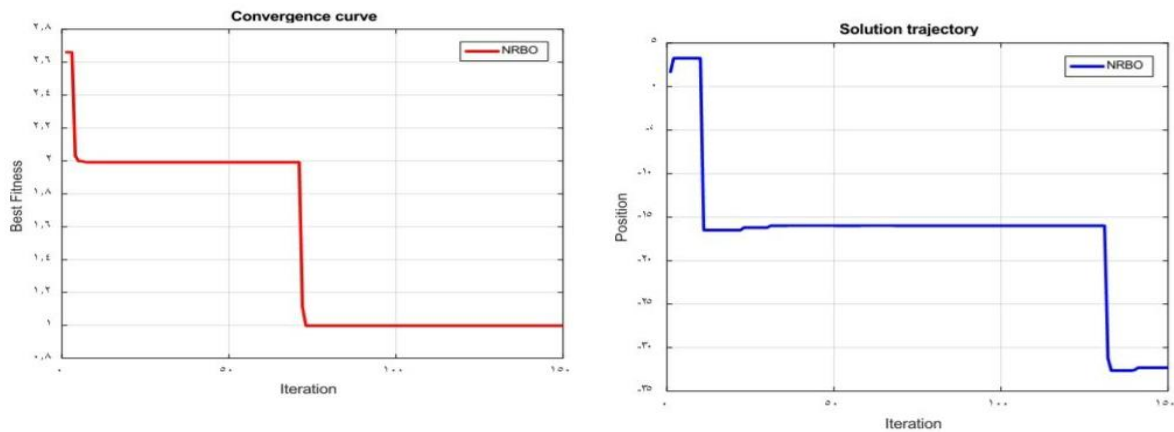


F12

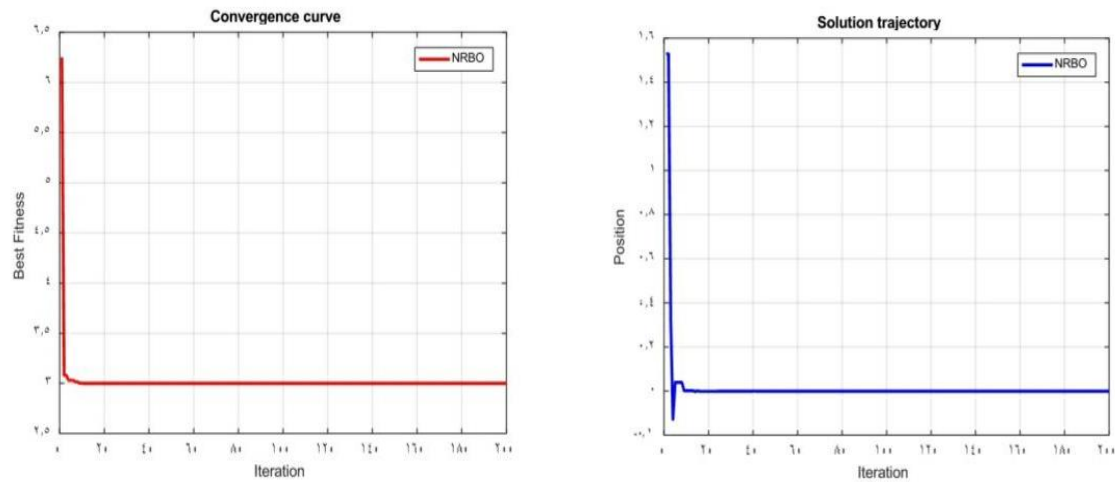
Figure III.5: Convergence Curve and Solution Trajectory for High-Dimensional Multi-modal Functions F9, F11, F12

Observations:

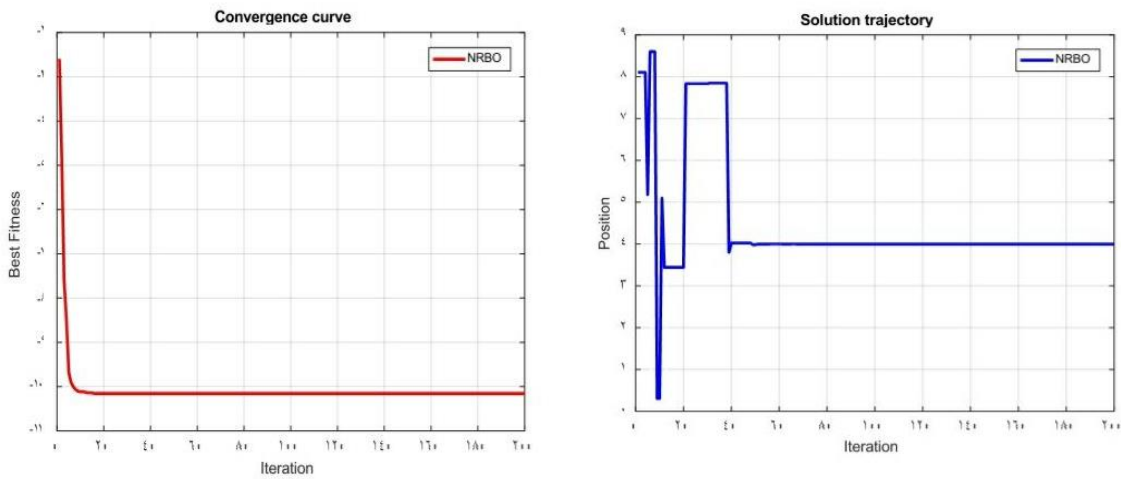
- ✓ The algorithm demonstrates rapid convergence, quickly approaching the optimal solution.
- ✓ The best solution stabilizes near zero, highlighting its effectiveness in achieving the final result.
- ✓ Notable early trajectory shifts suggest strong exploration capabilities within the search space.
- ✓ After the 8th iteration, the solution position remains unchanged, indicating premature termination of updates.
- ✓ Early stabilization of both curves reflects efficient exploitation of promising regions, with no oscillatory behavior.



F14



F18



F21

Figure III.6: Convergence Curve and Solution Trajectory for Low-Dimensional Multi-modal Functions F14, F18, F21

Observations:

- The convergence curve demonstrates a steady decline in fitness values. This pattern suggests consistent optimization efforts by the algorithm, followed by temporary stabilization.
- Both curves exhibit sudden, sharp transitions, highlighting the algorithm's capability to break free from local optima and discover more promising areas within the search space.
- A noticeable drop in the fitness value (1st curve) aligns with a significant shift in the solution's position (2nd curve). This synchronization confirms that the improvement stems from an actual relocation to a superior solution.

- In the final iterations, both curves stabilize at fixed values, signaling that the algorithm has achieved its optimal solution with no further enhancements.

Discussions on curves:

The NRBO algorithm demonstrates excellent performance in achieving fast convergence and stability. However, to ensure robustness and avoid premature convergence to suboptimal solutions, further testing on a diverse set of benchmark objective functions is recommended.

III.3. Part 2: Application

III.3.1. Presentation of our MANET Network

For simulation purposes, we designed a dynamic network consisting of N mobile nodes operating within a defined zone of dimensions $L \times H$. The network includes a sender (S) and a receiver (R). The simulated zone can represent various real-world environments, such as road networks, university campuses, or other mobility scenarios.

The figure below demonstrates an example of the network model used in our simulations.

The network comprises 10 mobile nodes, represented by red squares. Their movement directions are indicated by blue arrows, while the routing path is illustrated by a black line.

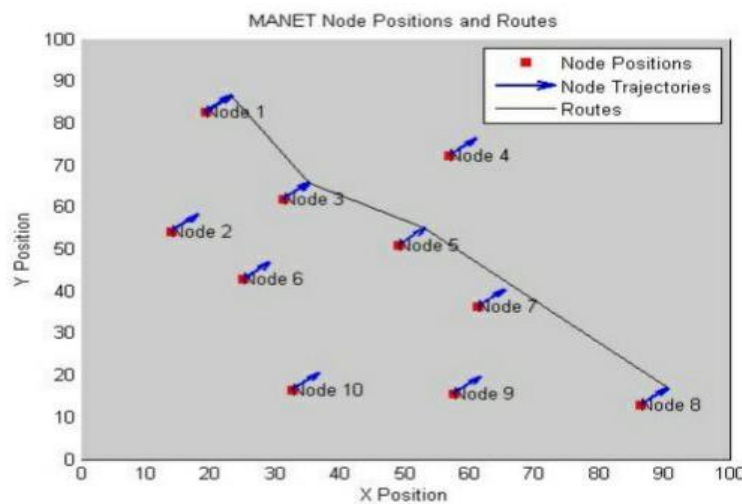


Figure III.7: Example of the MANET model used in our simulations.

The position NP of each node is determined by its (x, y) coordinates in the zone, and it can change its location over time (t): (NP_{ix}^t, NP_{iy}^t)

$$\begin{array}{cccccc}
 NP_{1x}^T & NP_{2x}^T & \dots NP_{ix}^T & \dots & NP_{Nx}^T \\
 NP_{1y}^T & NP_{2y}^T & \dots NP_{iy}^T & \dots & NP_{Ny}^T \\
 \\
 NP_{1x}^t & NP_{2x}^t & \dots NP_{ix}^t & \dots & NP_{Nx}^t \\
 NP_{1y}^t & NP_{2y}^t & \dots NP_{iy}^t & \dots & NP_{Ny}^t \\
 \\
 NP_{1x}^2 & NP_{2x}^2 & \dots NP_{ix}^2 & \dots & NP_{Nx}^2 \\
 NP_{1y}^2 & NP_{2y}^2 & \dots NP_{iy}^2 & \dots & NP_{Ny}^2 \\
 \\
 NP_{1x}^1 & NP_{2x}^1 & \dots NP_{ix}^1 & \dots & NP_{Nx}^1 \\
 NP_{1y}^1 & NP_{2y}^1 & \dots NP_{iy}^1 & \dots & NP_{Ny}^1
 \end{array}$$

We aim to identify the most efficient route for transmitting data from the transmitter to the receiver while minimizing the transmission distance.

Table III.5: Parameters used of modeling the MANET

Parameter	Value
N :Sensor node number	10
L :Length of the zone	100m
H :Height of the zone	100m
Rc :Communication range	30m
T :Duration of mouvement	10s

III.3.2. NRBO for Optimal MANET Routing :

Our proposed routing strategy for a Mobile Ad hoc NETWORK (MANET) utilizes the NRBO (Newton-Raphson-Based Optimization) metaheuristic algorithm. The process starts with the random initialization of candidate solutions (routes), which are then assessed using a predefined fitness function. The NRBO update mechanism iteratively refines these solutions, optimizing their performance until a specified termination condition is met.

III.3.2.1. Initialization:

The initial population can be represented as a matrix of size ($N_s \times (N - 2)$), where (N_s) is the number of solutions (rows) and ($N - 2$) is the number of intermediate nodes (columns), excluding the sender and receiver.

$$P = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_j \\ p_{N_s} \end{bmatrix}$$

Each solution path (p_j) is represented as a sequence of node indices, detailing the traversal route from the source (sender) to the destination (receiver).

Example : the following matrix presents an example of P, where the sender is $S=1$, the receiver is $R=8$, the number of nodes is $N=10$, and the number of solutions is $N_s=3$.

$$P = \begin{bmatrix} 4 & 9 & 3 & 0 & 0 & 0 & 0 & 0 \\ 2 & 5 & 3 & 10 & 6 & 4 & 0 & 0 \\ 10 & 3 & 5 & 4 & 9 & 2 & 7 & 6 \end{bmatrix}$$

The routing is :

- * For the 1st solution: 4-9-3 mean 1-4-9-3-8
- * For the 2nd solution: 2-5-3-10-6-4-0-0 mean 1-2-5-3-10-6-4-8
- * For the 3rd solution 10-3-5-4-9-2-7-6 mean: 1-10-3-5-4-9-2-7-6-8

III.3.2.2 Fitness function:

Our optimization problem focuses on minimizing the transmission distance of data between the sender and the receiver. By reducing this distance, we can also enhance:

✓ Reduces Energy Consumption:

Since nodes usually operate on battery power, minimizing transmission distances helps conserve energy. When data travels shorter hops, nodes avoid the need for strong signal amplification, which would otherwise drain more power. By reducing the distance data packets must travel, the network preserves battery life in individual nodes and improves overall energy efficiency.

✓ Reducing Overload and Congestion: In Mobile Ad Hoc Networks (MANETs), overload and congestion frequently arise when excessive traffic competes for limited network resources. By ensuring data packets travel shorter distances, the network can significantly lower the risk of congestion at intermediate nodes or along communication paths. Shorter transmission distances result in fewer hops, reducing contention for bandwidth and buffer space. This, in turn, decreases the likelihood of packet collisions, queuing delays, and buffer overflow. Thus, minimizing transmission distances helps distribute traffic more evenly across the network, alleviating potential overload and congestion.

Transmission Constraints: It is important to note that nodes in the network are only allowed to transmit data if the intended receiver lies within their transmission range.

Mathematical Formulation: Based on these principles, the objective function can be expressed mathematically as follows:

$$F(p) = F1 + F2 + F3 \quad (\text{Eq. III.1})$$

*F1 calculates the distance between two successive nodes (k and k+1)

$$F1 = \sum_{t=1}^T \sum_{k=1}^{(N2-2)} \sqrt{(NP_{p(k)x}^t - NP_{p(k+1)x}^t)^2 + (NP_{p(k)y}^t - NP_{p(k+1)y}^t)^2}$$

*F2 calculates the distance between the sender and the first node

$$F2 = \sum_{t=1}^T \sqrt{(S_x^t - NP_{p(1)x}^t)^2 + (S_y^t - NP_{p(1)y}^t)^2}$$

*F3 calculates the distance between the last node and the receiver

$$F3 = \sum_{t=1}^T \sqrt{(NP_{p(end)x}^t - R_x^t)^2 + (NP_{p(end)y}^t - R_y^t)^2}$$

III.3.2.3. Updating process:

The population is being updated through the NRBO (Newton-Raphson-Based Optimizer) It relies on four main stages: Initialization, Newton-Raphson Search Rule (NR.SR), Trap Avoidance Operator (TAO), and Computational Complexity.

III.3.2.4. Parameters used for simulation :

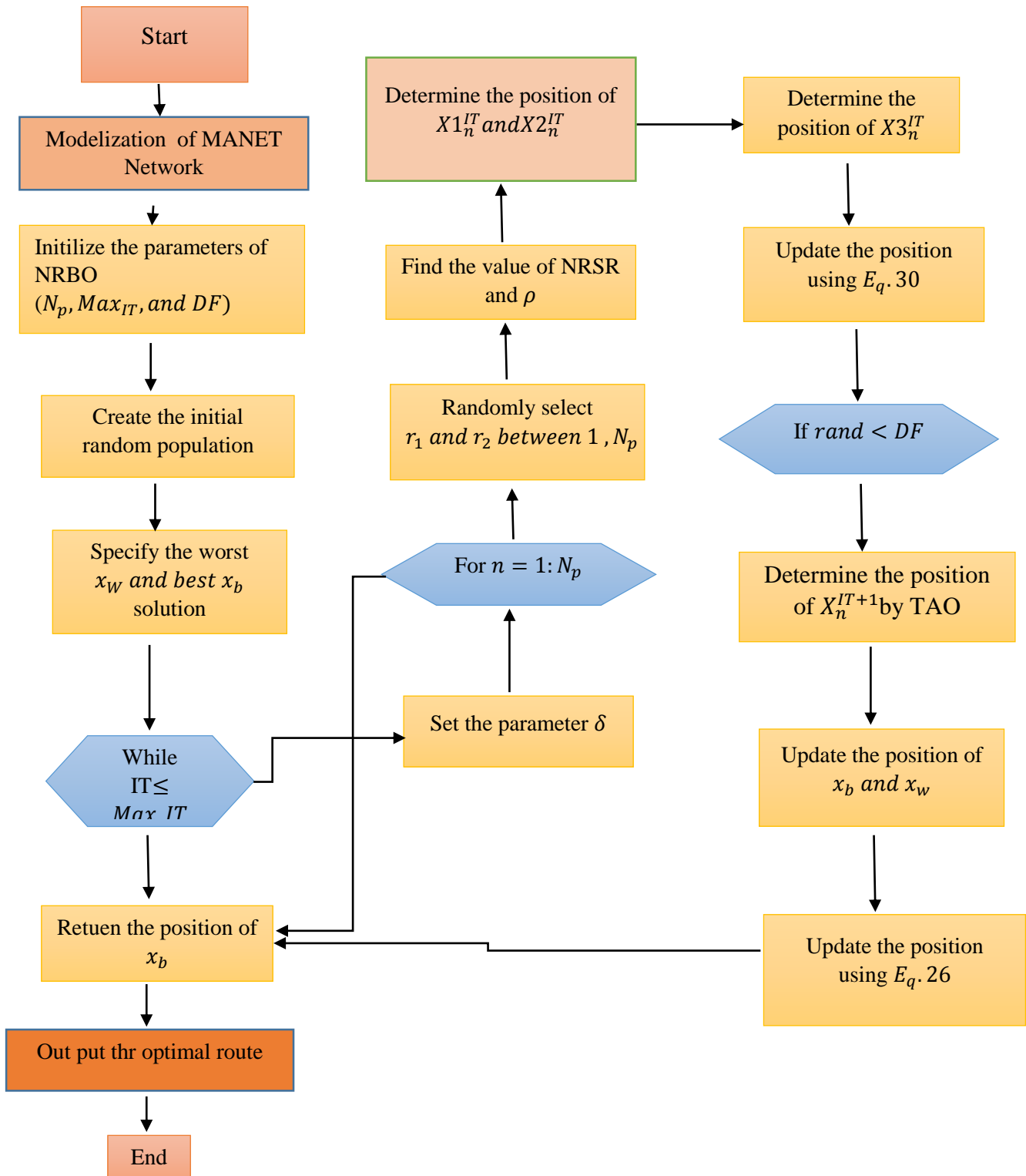


Figure III.8: Folowchart of NRBO algorithm

III.4. Simulation Results :

To evaluate the performance of our routing approach, which leverages the NRBO (Newton-Raphson-Based Optimization) method, we conduct extensive simulations by varying key parameters, including:

- The distance between sender and receiver
- The number of nodes in the network
- The number of candidate solutions
- The number of iterations

The results are presented through the following visualizations:

1. Network Topology Visualization: This figure illustrates the spatial distribution of nodes and highlights the optimal routing path identified by the NRBO for optimal MANET routing approach.

2. Convergence Analysis: This plot tracks the evolution of the objective function F (representing inter-node distances) across iterations, demonstrating its minimization over successive optimization steps.

These simulations aim to validate the efficiency and robustness of our proposed routing strategy under different network configurations.

III.4.1 Simulation 1

In the first simulation, we tested the algorithm under varying distances between the sender and receiver nodes: short, medium, and long. The goal was to assess the method's effectiveness in determining the optimal routing path, particularly over extended distances. This evaluation ensures the algorithm's robustness in maintaining efficient communication even when nodes are far apart.

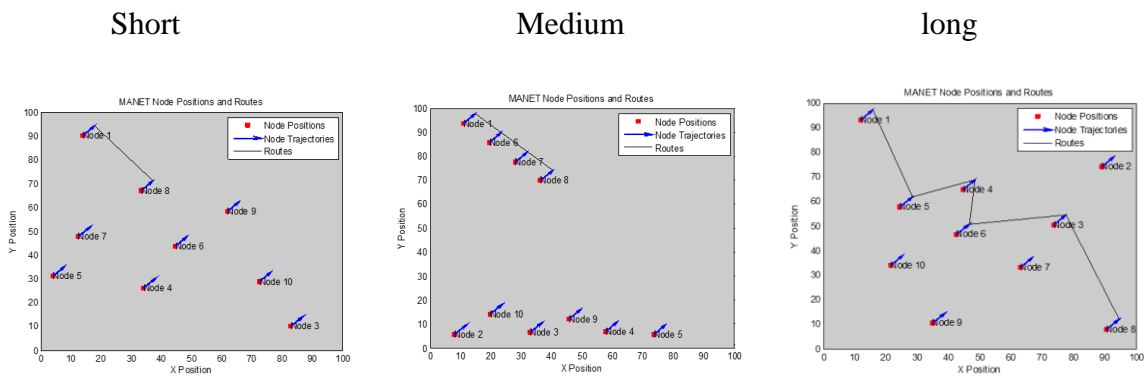


Figure III.9: Network with different distance between S and R.

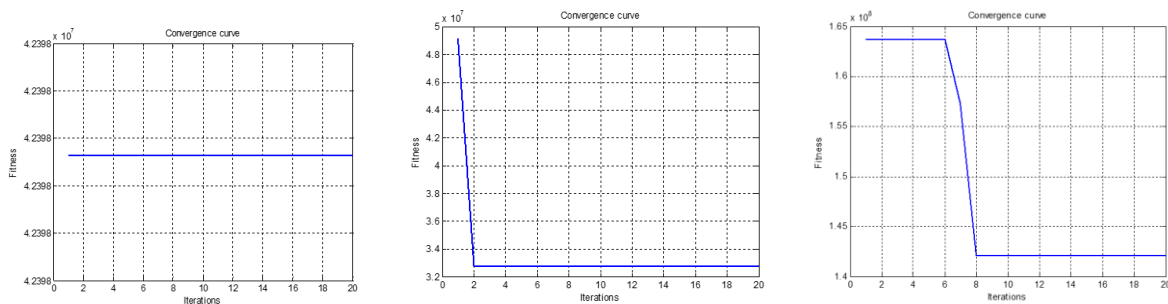


Figure III.10:Convergence curves with different distance between S and R.

The table summarizes the outcomes of Simulation 1, assessing solution effectiveness across three distance categories: short, medium, and long. Each entry includes:

- Distance Type: Short, Medium, Long
- Solution: A numerical sequence representing the optimal route.
- Fitness Value: A metric reflecting solution quality, where lower values suggest better performance .

TableIII.6. Results of Simulation1

Simulation 1	solution	Fitness
Short distance	0 0 0 0 0 0 0	4.2398e+07
Medium distance	6 0 0 0 0 0 0	3.2749e+07
Long distance	5 4 6 3 0 0 0 0	1.4211e+08

Discussion 1:

The results presented in Figures III.9 and III.10 highlight the following key observations:

✓ *Short Distance:* When the receiver node is within the direct communication range of the sender node, optimization requirements are minimal. The fitness value converges rapidly, suggesting that the optimal route is inherently simple due to the close proximity between the nodes.

✓ *Medium Distance:* In scenarios where the receiver node lies beyond the sender's immediate transmission range, the routing algorithm plays a critical role. The NRBO technique proves effective in determining the shortest path, showcasing its capability to efficiently route data through intermediate nodes. The convergence curve indicates that although the algorithm initially explores multiple possible paths, it consistently converges to the most efficient route exemplified by the path traversing nodes 6 and 7 to reach node 8.

✓ *Long Distance:* For extended distances, the algorithm maintains its effectiveness, though it requires more iterations to identify the optimal path. This is attributed to the greater complexity and higher number of potential routing paths. Despite this challenge, the algorithm demonstrates strong reliability and robustness in large-scale network topologies, as evidenced by its ability to converge to an optimal route such as the path passing through nodes 5, 4, and 6,3 before reaching node 8.

Conclusion 1:

The proposed NRBO algorithm demonstrates exceptional adaptability in optimizing MANET routing, efficiently adjusting to fluctuating network distances to maintain high-performance data transmission. Its strength lies in large scale, dynamic environments , where constant node mobility demands robust routing solutions.

Simulation results highlight the algorithm's intelligent search strategy exploring diverse suboptimal paths (initially with higher fitness values) before systematically refining its selection to converge on the optimal route. This balanced exploration-exploitation process ensures comprehensive path evaluation, significantly boosting network efficiency by consistently prioritizing the shortest and most reliable connections.

The performance of the proposed algorithm is clearly illustrated in Figures III.11 and III.12, which highlight its capability to determine the shortest path in networks of varying scales:

- Small-scale network (N=10): The algorithm efficiently computes the optimal path, routing data through nodes 5, 6, and 7 before arriving at node 8. This validates its effectiveness in smaller network configurations.
- Medium-scale network (N=20): Despite the higher complexity, the routing method maintains its efficiency, identifying the shortest path via nodes 2, 3, 4, and 5,6,7 to reach node 8. This demonstrates the algorithm's flexibility in moderately sized networks.
- Large-scale network (N=30): In extended network environments, the algorithm sustains reliable performance, even with additional intermediate nodes (e.g., 23, 21, 16, 7 and 8). This underscores the resilience of the NRBO for MANET routing approach in managing large scale networks without compromising transmission efficiency.

Overall, these results confirm the algorithm's scalability and consistent delivery of optimal routing solutions across different network sizes.

Conclusion 2:

The proposed routing method demonstrates robust adaptability and consistent reliability, performing effectively across networks of different sizes. It consistently generates optimal or highly efficient routing paths, ensuring fast and dependable data transmission regardless of network scale. This adaptability is especially beneficial in dynamic environments where node density and network conditions frequently change.

Extensive simulations confirm the algorithm's high performance. In compact networks, it quickly stabilizes on the shortest path with minimal computational effort. In larger, more complex networks, the method efficiently explores multiple routing possibilities while still achieving timely convergence to near-optimal solutions. This balanced approach enables comprehensive path analysis without compromising speed or overall network efficiency.

III.4.3. Simulation 3

This simulation investigated how the algorithm performs when using different quantities of candidate solutions specifically, 20, 50, and 100. The primary objective was to determine whether a larger pool of candidate solutions leads to improved results.

20 candidate solutions.

50 candidate solutions.

100 candidate solutions.

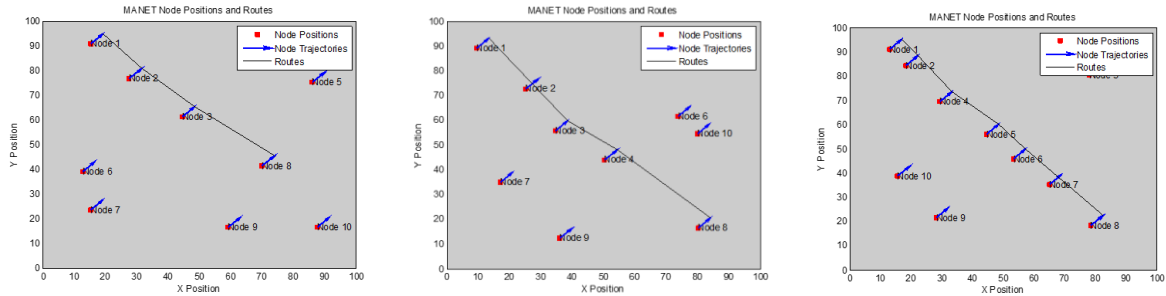


Figure III.13: Network with different number of candidate solutions.

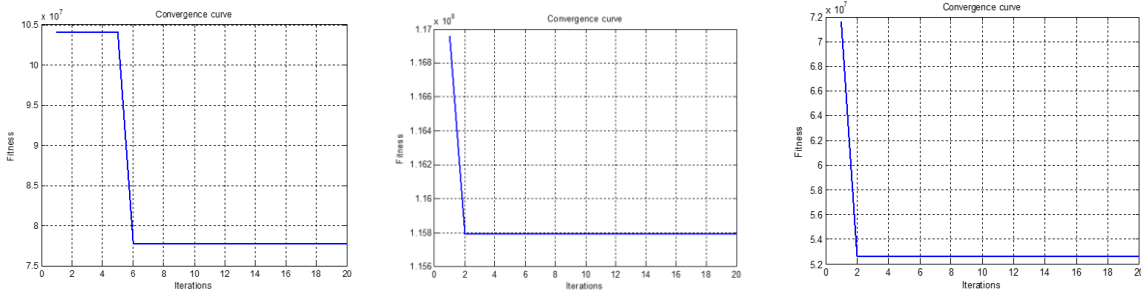


Figure III.14: Convergence curves with different number of candidate solutions.

Table III.8 : Results of Simulation3

Simulation 3	solution	Fitness
20 candidate solutions	2 3 0 0 0 0 0	7.7778e+07
50 candidate solutions	3 4 0 0 0 0 0	1.1579e+08
100 candidate solutions	2 4 5 6 0 0 0	5.2632e+07

Discussion 3:

The results shown in Figures III.13 and III.14 highlight two key findings:

1. Optimal Route Selection: The NRBO for optimal MANET routing algorithm consistently identifies the shortest possible path between the transmitter and receiver in all tested scenarios. This confirms the algorithm’s reliability in determining optimal routes, irrespective of the number of candidate solutions considered.

2. Faster Convergence with More Candidates: The convergence trends reveal that the algorithm achieves the best fitness value more rapidly when initialized with a higher number of candidate solutions. Notably, with 100 candidate solutions, the algorithm converges to the optimal route almost immediately. This indicates that increasing the candidate pool improves the algorithm's efficiency, enabling quicker discovery of the best routing path.

Conclusion 3:

The algorithm demonstrates strong performance regardless of the number of candidate solutions, consistently identifying the optimal route. Even with a limited pool of candidates, it maintains efficiency while reducing computational time. Additionally, increasing the number of candidate solutions can further improve its performance.

III.4.4. Simulation 4

In Simulation 4, we examined the algorithm's performance by varying the maximum iteration limits: 100, 150, and 200. The goal of this experiment was to assess whether increasing the maximum iteration count enhances the method's effectiveness.

100 maximum iterations.

150 maximum iterations

200 maximum iterations.

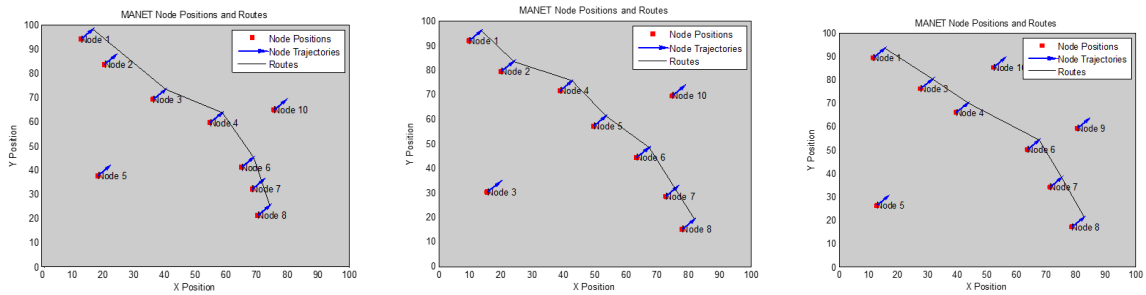


Figure III.15: Network with different number of maximum iterations.

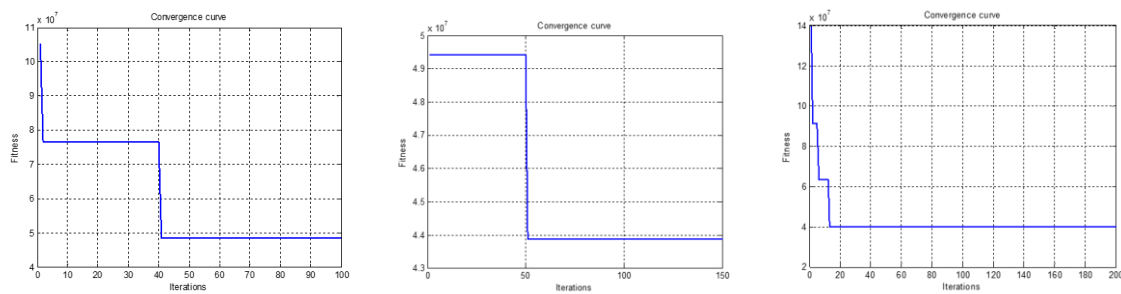


Figure III.16: Network with different number of maximum iterations.

TableIII.9: Results of Simulation 4

Simulation 4	solution	Fitness
100 maximum number of iterations	3 4 6 0 0 0 0 0	4.8538e+07
150 maximum number of iterations	2 4 5 6 0 0 0 0	4.3860e+07
200 maximum number of iterations	3 4 6 7 0 0 0 0	3.9766e+07

Discussion 4:

Results illustrated in figures III.15 and III. 16, indicate that:

✓ The NRBO for optimal MANET routing algorithm consistently identifies the optimal route with the shortest distance from the transmitter to the receiver across all tested scenarios. This demonstrates the algorithm's effectiveness in determining the shortest path.

✓ The convergence curves indicate that the algorithm stabilizes quickly from the initial iterations. This suggests that the algorithm is efficient and does not require a large number of iterations to find the optimal solution.

Conclusion 4:

Increasing the maximum number of iterations does not significantly improve the performance of the algorithm since the optimal route is found within the initial iterations. This implies that the algorithm is highly efficient and effective even with fewer iterations, minimizing computational time while maintaining optimal performance.

III.4.5. Summary

In summary, the proposed NRBO (Newton-Raphson-Based Optimized) metaheuristic routing method demonstrates strong effectiveness across varying sender-receiver distances, sustaining optimal routing performance due to its adaptive and robust convergence properties.

The method also performs reliably under different network sizes, maintaining high routing efficiency through its ability to adapt and converge effectively. Moreover, it exhibits high effectiveness and scalability across varying numbers of candidate solutions. The algorithm

consistently identifies the shortest data transmission path from sender to receiver, achieving faster convergence when initialized with a larger pool of candidate solutions.

Additionally, the algorithm reaches the optimal solution in minimal iterations, suggesting that increasing the maximum iteration count does not significantly improve performance.

III.5. Conclusion

This chapter presents the development of an enhanced routing protocol for Mobile Ad Hoc Networks (MANETs) based on the NRBO metaheuristic optimization technique. The primary goal of this protocol is to minimize the distance between the sender and the receiver by selecting the optimal path through a set of intermediate nodes.

We first evaluated the method's effectiveness by testing it with different benchmark functions. We observed promising and encouraging results, regarding the method's efficiency.

To evaluate the effectiveness of the proposed approach, a series of simulations were conducted. The results demonstrate that the enhanced protocol is capable of efficiently determining the optimal route, ensuring reliable and effective data transmission across various network scenarios ranging from small to large-scale environments while maintaining low computational complexity.

General conclusion

This master's thesis explores the enhancement of routing protocols in mobile ad hoc networks (MANETs) through the application of the Newton-Raphson-Based Optimization (NRBO) method. The optimization process is driven by the geographic positions of communication nodes, with a focus on identifying the shortest and most efficient routing paths. The research first examines the theoretical foundations of the NRBO approach, followed by an in-depth analysis of MANET characteristics, and concludes with simulated results validating the proposed method's efficacy.

Based on the positive results obtained from the function test, which demonstrated the efficiency and accuracy of the proposed method in reaching optimal solutions, it became both logical and motivating to extend the experimentation and apply it to the NRBO system. These results provided a strong foundation that supports the feasibility and effectiveness of the proposed methodology, encouraging us to implement it in a more complex and realistic environment.

Simulation outcomes demonstrate that the NRBO routing algorithm consistently achieves optimal or near-optimal path selection across varying network sizes. Its adaptive optimization capability ensures efficient route determination, even with limited computational resources (e.g., restricted candidate solutions and iterations). This equilibrium between performance and computational efficiency positions NRBO as a robust routing solution for dynamic MANET environments.

The findings affirm the successful analysis of the NRBO algorithm in telecommunications, particularly for MANET routing protocols. The technique effectively accomplishes its primary objective of determining the shortest communication paths between senders and receivers in all tested scenarios. These results underscore the reliability and efficiency of NRBO-based routing in improving MANET performance.

Future research directions include investigating alternative metaheuristic approaches, integrating additional network constraints, and expanding the applicability of NRBO to other telecommunications domains.

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- [15] Furthermore, the chapter has introduced the NRBO (Newton-Raphson- Based Optimization) technique, elaborating on its conceptual inspiration, mathematical formulation, and algorithmic structure. In the following chapter, the discussion will transition to examining the fundamental

principles of MANET (Mobile Ad Hoc Network) networks.

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