Intelligent Routing Protocols Using Machine Learning

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Abstract

Routing serves as a cornerstone of network management, pivotal in determining the optimal path for data transmission. This research endeavor endeavors to scrutinize and assess improved routing algorithms customized for both wired and wireless networks. The inquiry encompasses a meticulous examination of contemporary routing algorithms deployed in these networks, aimed at gauging their effectiveness and operational efficiency. Specifically, the investigation delves into the OSPF (Open Shortest Path First) protocol tailored for wired networks and the AODV (Ad hoc On-Demand Distance Vector) protocol designed for wireless networks. These protocols are acknowledged as the most fitting for their respective network domains. The core thrust of this inquiry resides in a comprehensive analysis of routing algorithms employed in both wired and wireless networks, with particular attention directed towards OSPF and AODV. Elaborate elucidations regarding the foundational characteristics of these protocols are provided in ensuing sections. Additionally, the research explores shared traits observed in wired and wireless routing algorithms, alongside deliberating on the potential advantages of integrating machine learning methodologies to further enrich and optimize these algorithms. Through this investigative journey, the research endeavors to contribute to the progression of routing protocols, with the overarching goal of fostering more streamlined and dependable network communication.

Keywords**:** Routing Protocols, 5.Artificial Intelligent, Machine Learning, Swarm Intelligence

1. Introduction

The essential goal of communication networks is to provide access to essential information anytime and anywhere [1]. These networks are commonly categorized into two types: wired and wireless networks, based on their characteristics and connectivity methods. Wired networks utilize various types of cables, such as coaxial cable, Ethernet, optical fiber, and twisted pair cables [2]. These wired organizations offer a few benefits, including the quickest information move speeds among all organization types, resistance to impedance and changes, and a more powerful security framework contrasted with remote organizations. Notwithstanding, they additionally accompany a few disadvantages, for example, restricted versatility and higher establishment costs.

Remote systems administration is a broadcast communications procedure generally utilized in homes, organizations, and broadcast communications organizations. It permits gadgets to associate without the requirement for actual links, accordingly wiping out the significant expenses related with wiring various gadgets in discrete areas [3]. Wireless networks operate through radio communication, enabling effective data transmission and reception.

Wireless networks encompass a diverse array of types, each serving distinct purposes and operating in varied environments. Personal Area Networks (PANs) link devices within close proximity, typically within a few meters, facilitating connectivity for gadgets like smartphones and wearables. Local Area Networks (LANs) extend this connectivity to a broader area, such as within a building or campus, often employing Wi-Fi technology. Metropolitan Area Networks (MANs) cover larger geographic regions, like cities, using technologies such as WiMAX or LTE for widespread wireless access. Wide Area Networks (WANs) further expand this reach across vast distances, spanning cities, countries, or continents, often relying on cellular networks, satellite links, or microwave connections for global communication. Cellular networks provide mobile services through a network of base stations, enabling voice calls, messaging, and internet access over long distances. Wireless Ad Hoc Networks (MANETs or WANETs) operate without a fixed infrastructure, with nodes dynamically routing data to establish decentralized communication, ideal for scenarios where infrastructure deployment is challenging or impractical. Global Area Networks facilitate communication on a global scale, often utilizing satellite systems for international internet access, broadcasting, and remote sensing. Space Networks enable communication between devices in space, supporting satellite communication, navigation, Earth observation, and scientific research. Each type of wireless network offers unique advantages tailored to specific connectivity requirements, encompassing factors like coverage area, mobility, data rate, and reliability. [4].

Wireless networks offer both advantages and disadvantages. On the positive side, they are more cost-effective than wired networks in terms of installation, maintenance, and overall cost. They provide mobility and versatility, allowing easy setup and disassembly as needed. Additionally, wireless networks enable quick and convenient access to the internet and workspaces [5].

While wireless networks offer numerous benefits, it's essential to acknowledge their drawbacks as well. One significant concern is their potentially lower reliability and security compared to wired networks. Without physical cables to safeguard data transmission, wireless networks may be more susceptible to unauthorized access and data breaches.

Additionally, wireless networks often face limitations in terms of bandwidth. This constraint can make them more vulnerable to issues like jamming and interference, which can degrade signal quality and disrupt communication. As more users connect to a wireless network, the shared airwaves used for signal transmission can become congested, leading to decreased performance for all users.

Moreover, wireless networks are inherently subject to environmental factors such as physical obstacles, electromagnetic interference, and signal attenuation over distance. These factors can further impact reliability and performance, especially in densely populated areas or environments with significant radio frequency interference.

Furthermore, the mobility of wireless devices introduces challenges in maintaining consistent connectivity, as devices may move in and out of coverage areas or encounter signal dead zones. This mobility factor requires robust mechanisms for seamless handover between network access points to prevent service interruptions.

Lastly, the deployment and maintenance of wireless networks can be more complex and costly than wired counterparts, requiring careful planning of access point placement, frequency management, and security protocols to mitigate potential risks and ensure optimal performance.

2. Routing Protocols

Routing is a critical process in computer networks that plays a fundamental role in determining the most efficient paths for forwarding data packets from their source to their intended destination [5]. To accomplish this, different directing conventions have been grown, each customized to suit various kinds of organizations. These conventions can extensively be isolated into two classifications: one intended for wired networks and one more for remote organizations [6].

With regards to wired networks, directing conventions are additionally partitioned in view of their particular purposes into Outside steering conventions and Interior directing conventions. Outside directing conventions center around trading steering data between various independent frameworks, working with correspondence between networks worked by various associations or elements. Then again, Inner directing conventions are liable for overseeing steering inside a solitary independent framework, guaranteeing productive information move inside that specific organization [7].

Routing protocols can likewise be characterized in light of their functional systems. Distance Vector steering conventions work by iteratively computing the total pathway loads, frequently depending on calculations, for example, Bellman-Passage or comparable ones. Conversely, Connection State-based steering conventions adopt a more thorough strategy by building a total guide of the organization geography prior to deciding the ideal ways for information transmission. Moreover, there are Crossover steering conventions that join highlights from both Distance Vector and Connection State conventions, offering an equilibrium of advantages from the two methodologies [3].

Another classification criterion is based on the behavior of routing protocols in relation to IPv4 address space. Classful Routing Protocols are limited in their understanding of IP address classes and can only handle standard networks from Classes A, B, or C. In contrast, Classless Routing Protocols possess a more flexible understanding of IP address spaces, allowing them to deal with non-standard networks that may result from network fragmentation [8].

Furthermore, routing protocols may operate at different layers within the OSI communication model, namely the second (Data Link Layer), third (Network Layer), or seventh (Application Layer). Each layer plays a specific role in data communication and management, and routing protocols can be designed to operate effectively at any of these layers [9].

Figure (1) serves as a concise reference for understanding the different routing protocols and their characteristics, making it easier to select the appropriate routing protocol based on specific network requirements and criteria.

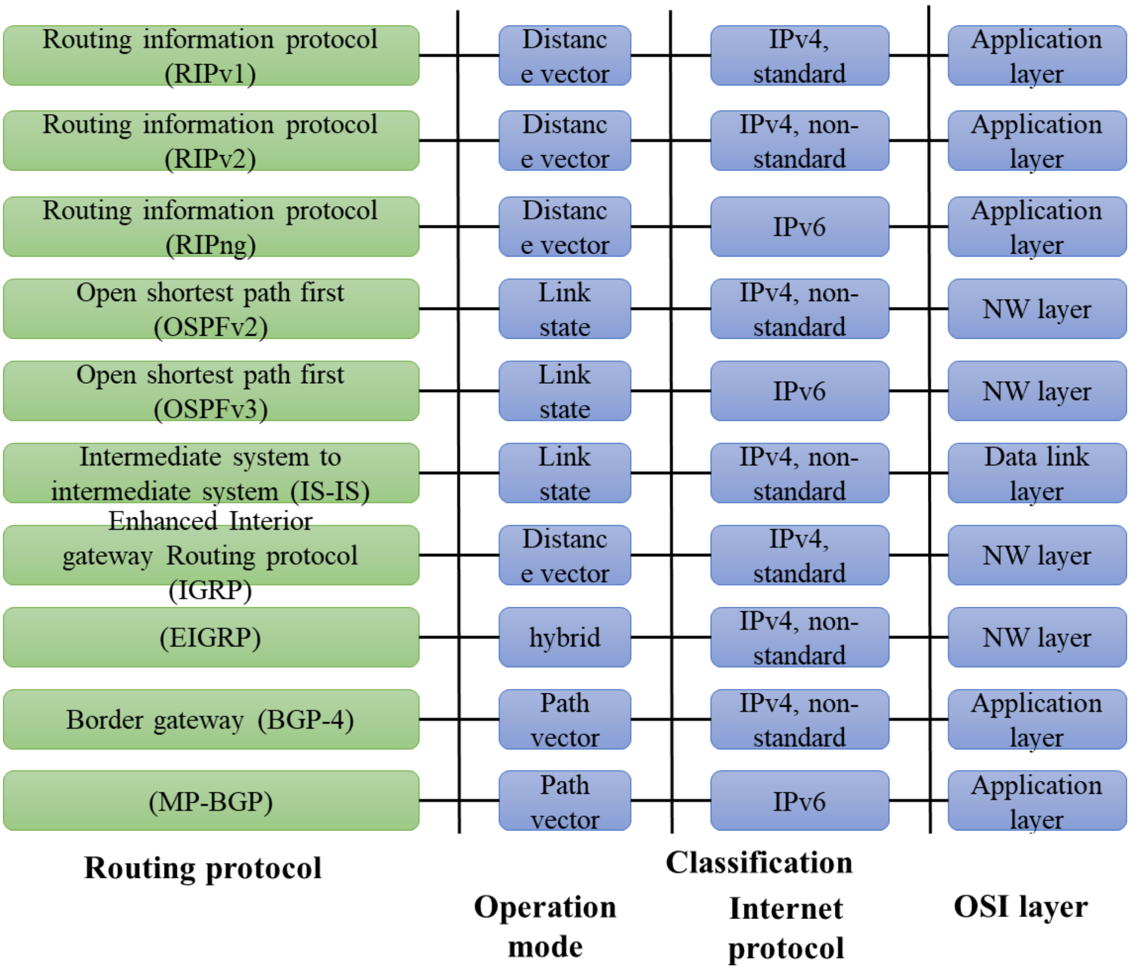

Figure 1: Wired Routing Protocol [10]

Wireless network routing protocols can be categorized into two main types: Table-driven and On-demand protocols [11]. Table-driven conventions make and keep up with directing tables ahead of time, persistently refreshing them to guarantee they have the most recent steering data. Then again, On-request conventions ascertain courses just while required, diminishing the above of keeping up with directing tables. After some time, this arrangement has been additionally extended to incorporate three gatherings: Proactive, Receptive, and Mixture conventions. Proactive conventions build steering tables proactively, Responsive conventions decide courses on-request or when expected, while Cross breed conventions show a mix of both proactive and receptive ways of behaving [12].

In addition, remote routing protocols can likewise be grouped in light of the organization geography they handle. The primary sort is the Level geography, which thinks about the whole organization geography all in all. The subsequent sort is the

Progressive geography, which deals with the organization in a progressive way, frequently partitioning it into subnets or levels of association. While contrasting steering conventions in portable organizations, different elements are thought about, for example, the geography structure, way accessibility, recurrence of updates, stockpiling prerequisites, defer in course revelation, and versatility. These viewpoints are fundamental in choosing the most reasonable directing convention for a particular remote organization climate (See Figure 2).

Protocol name	Algorithm work	Network Topology
Wireless Routing Protocol WRP	proactive	Flat
(GSR) Protocol	proactive	Flat
(FSR) Protocol	proactive	Flat
(STAR) Protocol	proactive	Hierarchical
(DREAM) protocol	proactive	Flat
(MMWN) Routing Protocol	proactive	Hierarchical
(CGSR) Protocol	proactive	Hierarchical
(HSR) Protocol	proactive	Flat
(OLSR) Protocol	proactive	Flat
(TBRPF) Protocol	proactive	Flat
(AODV) Routing Protocol	Active	Flat
(DSR) Protocol	Active	Flat
(LMR) Protocol	Active	Flat
(ROAM) Protocol	Active	Flat
(TORA) Protocol	Active	Flat
(ABR) Protocol	Active	Flat
(SSA) Routing Protocol	Active	Flat
(RDMAR) Protocol	Active	Flat
(LAR) Routing Protocol	Active	Flat
(ARA) Protocol	Active	Flat
Flow Oriented Routing Protocol FORP	Active	Flat
Cluster-based Routing Protocol CBRP	Active	Hierarchical
Zone Routing Protocol ZRP	Hybrid	Hierarchical
(ZHLS) Routing Protocol	Active	Hierarchical
(SLURP) Routing Protocol	Active	Hierarchical
(DST) Routing Protocol	Active	Hierarchical
(DDR) Protocol	Active	Hierarchical

Figure 2: Wireless Routing Protocol

3. Routing Problems

A routing protocol plays a critical role in ensuring efficient data transfer between endpoints across a network, including multicasting to groups of nodes [13]. The network must be capable of handling varying loads, both heavy and light, as well as adapt to situations of overload. Additionally, the protocol should be able to cope with fluctuations in traffic patterns, prevent routing oscillations and loops, and swiftly respond to resource demands. Ensuring Quality of Service (QoS) is essential, and the protocol should also be able to plan for reserved traffic [14].

Moreover, the directing convention needs to work really in a multi-provider climate, where certain framework state information probably won't be open beyond unambiguous provider regions. It ought to oblige both start to finish and multicast traffic to meet assorted correspondence prerequisites. Accomplishing these targets will add to a vigorous and dependable organization framework [14].

4. Open Shortest Path First

OSPF, an acronym for Open Shortest Path First, is a routing algorithm commonly employed in Internet networks. This algorithm operates by utilizing link-state information within individual regions, which collectively form a hierarchical structure. Its foundation lies in Dijkstra's algorithm, enabling the computation of the shortest path tree for each area of the network [15].

Dijkstra's calculation is a strategy utilized to track down the briefest ways between hubs in a chart, explicitly from a source hub to an objective hub. The calculation ends once it distinguishes the briefest course to the objective hub [6]. One of its primary advantages is its applicability in determining the Open Shortest Path First (OSPF) [15].

However, the algorithm also comes with some drawbacks. It performs a blind search, leading to considerable processing time wastage. Additionally, it cannot handle negative edges in the graph and is prone to generating acyclic graphs or loops. Moreover, in certain cases, it may not always find the correct shortest path [15].

5. Artificial Intelligent and Machine Learning

Artificial intelligence (AI) techniques offer effective tools for optimizing multiple conflicting goals and accurately estimating network parameters simultaneously. On the other hand, machine learning (ML) aims to automatically learn environment properties and quickly adapt behaviors accordingly. When it comes to routing algorithms, various properties are taken into account, such as memory limitations, communication costs, and energy restrictions. However, the suitability of many ML strategies for the networking domain remains unclear [16].

AI and ML leverage historical traffic data to learn and develop optimal routing configurations for future conditions [17]. Within the realm of routing protocols, intelligent algorithms like Ant Colony Optimization (ACO), Reinforcement Learning (RL), Genetic Algorithms (GA), Fuzzy Logic (FL), and Neural Networks (NNs) are commonly employed [16]. Figure (3) shows AI methods applied to address routing challenges.

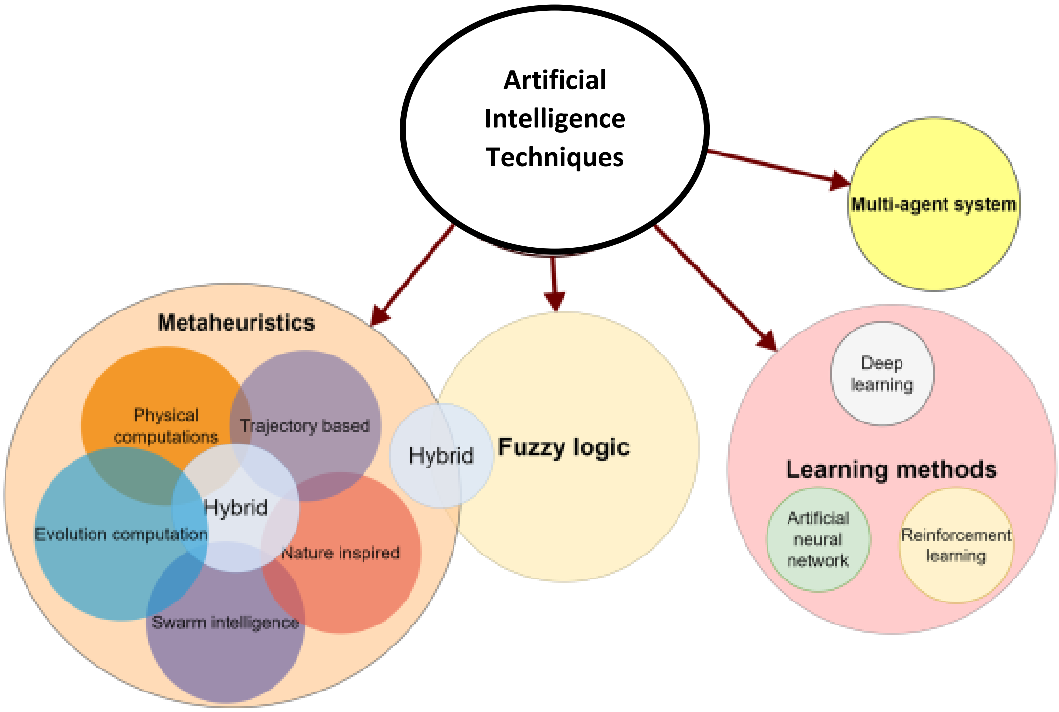

Figure 3: AI Techniques used in Routing [18]

5.1 Metaheuristics

Metaheuristics allude to techniques that guide the hunt interaction productively to investigate the inquiry space and track down close ideal arrangements. These calculations can be arranged in various ways. One order incorporates direction based approaches, which plan to track down a solitary ideal arrangement, like reproduced tempering [19]. Another category is population-based approaches, where multiple solutions are utilized across the search space to reach the final solution [20].

Swarm Intelligence (SI) is a prominent computational intelligence method used to address complex problems. SI involves the collective study of individual behaviors within a population interacting in the same environment. Inspiration is often drawn from nature, particularly biological systems [21]. These procedures advance data dividing between people and support methodologies for self-association, learning, and co-development during cycles to accomplish high effectiveness. The straightforwardness of change that people follow empowers connections among them, and as there is no focal foundation to show their way of behaving, the populace can trade related information utilizing different informing frameworks [22].

5.2 Learning Methods

One of the most momentous characteristics of people and creatures is their ability to learn. 'Learning' with regards to simulated intelligence alludes to the capacity to gain new information naturally and constantly, without express programming. Artificial

Neural Networks (ANNs), Reinforcement Learning (RL), and Deep Learning (DL) are examples of AI techniques that involve learning. ANNs have achieved considerable success in tackling complex challenges by mimicking biological neural networks and human characteristics [23]. They track down application in different regions, like expectation, approval, advancement, bunching, time series examination, and example acknowledgment. Various structures of ANNs exist, including spiral premise capability organizations, multilayer perceptrons (MLP), and recurrent neural networks (RNNs) [24].

RL, a part of artificial intelligence, rotates around how smart specialists ought to work in a climate to boost combined rewards. The growing experience in RL happens through the association of learning objects with their current circumstance, where they look to learn through experimentation [25].

DL, then again, is an alluring simulated intelligence capability that can learn without human oversight, utilizing unstructured and unlabeled information. It imitates the mind's information handling and makes designs for navigation. DL is viewed as a general learning plan, broadly applied to tackle a great many issues across different applications [26]. Its unmistakable component lies in addressing highlight extraction at numerous progressive levels.

DL's versatility allows it to address situations such as difficulties in explaining expertise, changing problem solutions over time, lack of human experts, and handling problems with vast sizes beyond limited reasoning capabilities. Given its broad usage, DL is often referred to as the Universal Learning Technique [26].

5.3 Fuzzy Logic (FL)

Fuzzy Logic (FL) is another AI technique that emulates human decision-making processes and finds application in handling uncertain reasoning and managing incomplete information. In FL frameworks, choices depend on a "truth esteem" that lies somewhere in the range of 0 and 1 . The enrollment of fluffy sets can differ inside this reach. Methods like infuzzification, most extreme, and mean-of-maxima are instances of how fluffy set enrollment is used [27].

5.4 Multi-Agent System (MAS)

In situations where complex issues demonstrate troublesome or even unimaginable for a solitary specialist or solid framework to deal with, (MAS) assume a critical part. MAS alludes to self-coordinated wise frameworks that reenact certifiable spaces with different unmistakable parts connecting in complex ways. Understanding framework level ascribes from individual part properties isn't clear. MAS comprises multiple autonomous intelligent entities called agents, capable of collaborating to address challenges that surpass the abilities of any single agent. It falls within the domain of Distributed AI [28].

The inborn capability of MAS lies in its ability to learn and settle on independent choices, empowering specialists to handle issues with more prominent adaptability. Specialists secure new information by connecting with adjoining specialists or the climate. This information is then used to pursue informed choices and make moves in the climate to determine relegated errands. The meaning of MAS is confirmed by its great many applications [29].

6. Basic Workflow for machine learning in networking

Here are the fundamental steps for enhancing the network's performance, as depicted in Figure (4)

Step 1. Selection of Routing Algorithms: The process begins by selecting suitable routing algorithms for both the wired and wireless networks.

Step 2. Problem Identification and Analysis: The selected routing algorithms are executed, and their performance is thoroughly analyzed to identify potential drawbacks. The study focuses on various efficiency parameters, including energy consumption reduction and network lifetime enhancement for data relay.

Step 3. Formulating Mathematical Models: To facilitate problem-solving, the identified issues are translated into mathematical models represented by equations.

Step 4. Utilizing Machine Learning: Machine learning techniques are employed to address the identified problems. The appropriate machine learning methods are chosen based on the specific nature of the issues.

Step 5. Application of Machine Learning Techniques: The selected machine learning techniques are applied to the network to optimize its performance.

Step 6. Evaluation: The performance of the modified routing algorithms is evaluated by comparing them with the original algorithms. This evaluation process helps assess the improvements achieved through the application of machine learning techniques.

In summary, this approach involves selecting appropriate routing algorithms, understanding and identifying the network's challenges, converting the issues into mathematical models, utilizing machine learning techniques, and finally, evaluating the enhancements made to the routing algorithms to optimize the network's performance.

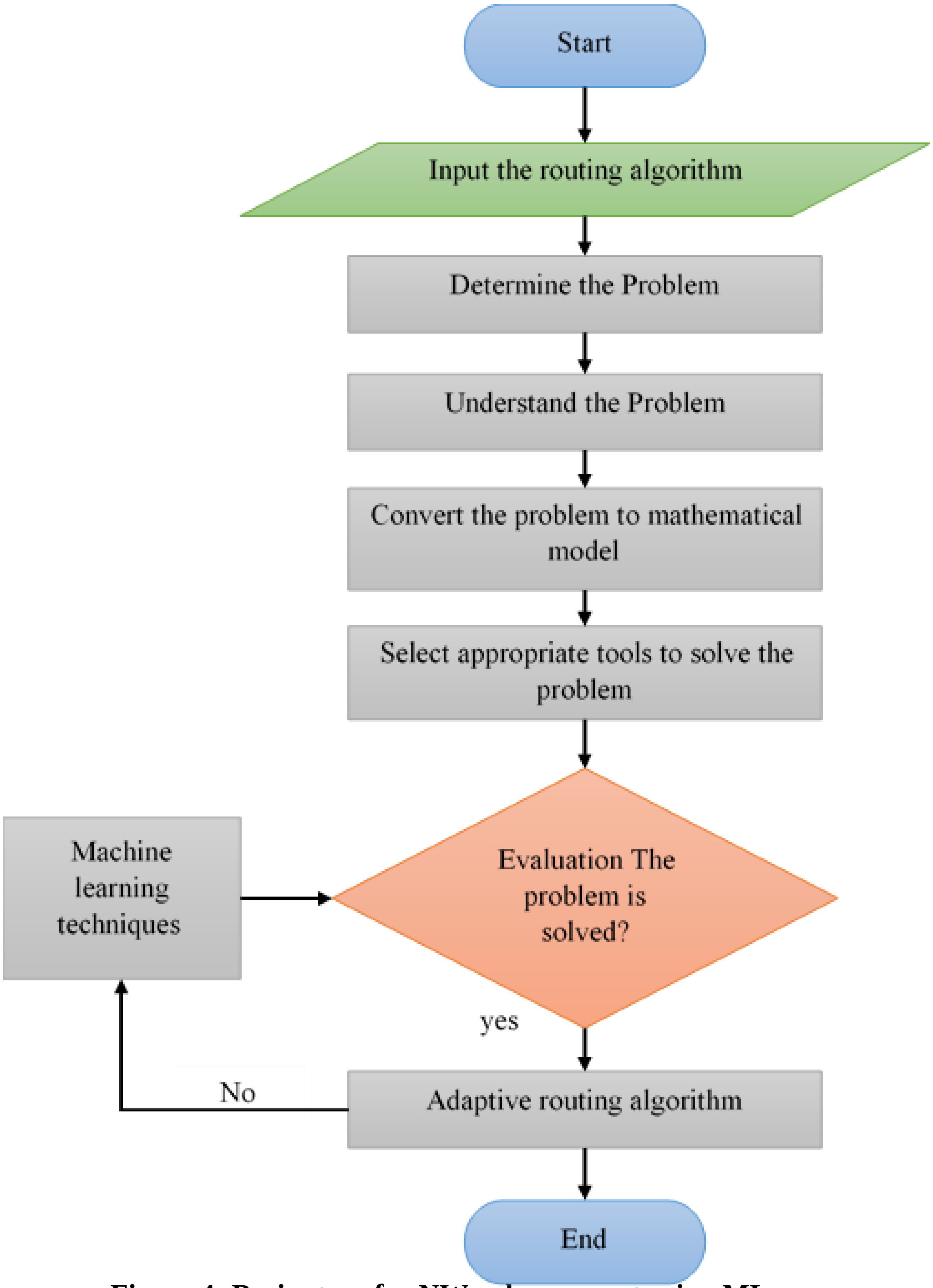

Figure 4: Basic steps for NW enhancement using ML

7. Previous Works

Table (1) presents a comprehensive overview of various research studies focusing on Artificial Intelligence (AI) techniques, particularly metaheuristics, applied to wireless sensor networks (WSNs). These AI-based strategies play a critical role in efficiently solving complex optimization problems and finding near-optimal solutions in WSNs. Metaheuristics are versatile algorithms that guide the search process within the network's search space, enabling the discovery of optimal or near-optimal solutions.

The studies listed in the table explore different metaheuristic algorithms, each with specific objectives and simulation tools used for evaluation. The research efforts span both centralized and distributed approaches, accommodating various mobility scenarios, such as static and mobile nodes. The performance metrics considered in these studies cover a wide range of key aspects, including energy efficiency, network lifetime, packet delivery ratio, latency, throughput, load balancing, and more.

By utilizing AI techniques like PSO, Bee Colony, Genetic Algorithms (GAs), GSA, and others, researchers aim to enhance the performance and energy efficiency of WSNs. These metaheuristics enable the intelligent coordination and decision-making of sensor nodes, making WSNs more robust, adaptive, and capable of handling various real-world challenges effectively.

Table 1: Previous works Comparison

Ref.	Algorithm	Objective	Simulation Tool	Centralized/ Distributed	Mobility	Performance Metrics
[30]	EPMS	Augmenting network lifetime	Real deployment	Distributed	Static with MS	Energy Utilization, Alive Hubs, Normal conveyance delay.
[31]	GWO	Balance energy utilization and burden	MATLAB	Centralized	Static	First door bite the dust, First hub pass on, Half hubs alive, Standard deviation of burden.
[32]	SICROA	Improve directing execution	NS2	Distributed	Mobile	Start to finish delay, Parcel conveyance proportion.
[33]	PSO	Boosting network lifetime	MATLAB	Distributed	Static	Network lifetime, Energy utilization.
[34]	iABC	Streamlining energy proficiency of an organization	NS2	Centralized	Static	Energy utilization, Parcel conveyance proportion, WSN lifetime, Throughput.
[35]	IABCP	Settling lopsided organization burden and energy use	MATLAB	Centralized	Static with MS	Network life cycle, Dead hubs, Normal excess energy, First hub dead, Normal single-bounce distance.
[36]	PSO	Diminishing control above and energy utilization	MATLAB	Distributed	Static with MS	Start to finish Deferral, Bundle Conveyance

						Proportion, Energy Utilization.
[37]	PSO	Keeping away from energy openings	MATLAB	Distributed	Static with MS	Energy utilization, Organization lifetime, Normal number of jump.
[38]	PUDCRP	Adjusting energy utilization	MATLAB	Distributed	Static	Remaining energy, Getting through hubs, Number of bundles got by the BS.
[39]	GMDPSO	Upgrading network execution	MATLAB	Distributed	Static	Combination, Normal number of alive hubs, First and Last hub bite the dust, Normal number of unClustered hubs, Throughput.
[40]	PSO	Successfully diminishing energy utilization	MATLAB	Centralized	Static	Network lifetime, Energy utilization, Idle sensors, Bundles got by BS.
[41]	PSO	Further developing lifetime of sensor hubs	MATLAB	Centralized	Mobile (quasistationary)	Remaining energy, Standard deviation, Alive and Dead hubs, Throughput.
[42]	ESO-LEACH	Upgrading network life range	Python	Distributed	Static	Energy dissemination, Organization lifetime.
[43]	PSO E-OEERP	Energy Effective	NS2.32	Distributed	Static	Load Adjusting Proportion, Energy Utilization, Bundle Conveyance Proportion, Throughput, Organization Lifetime.
[44]	Bee Colony (MOFPL)	Boosting lifetime of sensor hubs	MATLAB	Centralized	Static	Network Lifetime, Energy Utilization.
[45]	Bee Colony (iABC)	Energy-effective	NS2	Centralized	Static	Throughput, Bundle conveyance proportion, Energy

						effectiveness, WSN lifetime.
[46]	Bee Colony (DSABC)	Further developing organization lifetime	C++	Distributed	Static	Normal leftover energy, Standard deviation, Count of information bundles got.
[47]	Bee Colony	Energy utilization balance	MATLAB	Distributed	Static	Energy utilization, Measure of endurance hubs, Organization unwavering quality.
[48]	Bee Colony (CDABC)	Decreasing energy costs	OMNeT++	Distributed	Static	Alive hubs, First Hub Bite the dust, Dormant/dead hubs, Organization lifetime.

8. Conclusion

In this comprehensive survey, we have conducted an in-depth examination of wired and wireless routing protocols. Our study revolves around the enhancement techniques employed by these protocols to optimize network capacity and resource utilization. The research aims to shed light on the improvements made to various protocols in both wired and wireless networks. Given the diverse shortcomings found in these protocols, selecting the most suitable one for specific circumstances can be challenging. Additionally, the network landscape presents various challenges that must be addressed, paving the way for broader utilization of these protocols in the future.

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