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Optimal Routing in Wireless Sensor Networks for Advancing IoT Efficiency and Sustainability using Enhanced Ant Colony Algorithm with machine learning approaches

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Abstract: - This research study aims to investigate the incorporation of machine learning tools, such as Q-learning, Genetic Algorithms, Unsupervised Learning, and Ensemble Learning, into Enhanced Ant Colony Algorithm to assess the impacts of such incorporation on the WSN's performance. Ten experimental trials were conducted on each to analyze the accuracy, precision, and F1 score results. It was observed that Q-learning achieves an average accuracy of 0.867; precision of 0.842; and F1 score of 0.854, making it highly adaptable and efficient in making routing decisions. The GA presented average accuracy of 0.833; precision of 0.812; and F1 score of 0.821 which show that the tool is highly robust in evolutionary optimization. Unsupervised learning machine performances indicate that the mean accuracy, precision, and F1 score for the model are 0.875, 0.856, and 0.865, respectively . As for ES with multi source models, the model showed the highest performance of 0.898, 0.882, and 0.891 in accuracy, precision, and F1 score, respectively . This study is thus very valuable in the backend regarding application of machine learning tools into routing optimization algorithms and efforts geared towards WSN efficiencies and sustainability..

Keywords: Wireless Sensor Networks, Routing Optimization, Machine Learning Techniques, Enhanced Ant Colony Algorithm, IoT Applications.

I. INTRODUCTION

Wireless sensor networks , commonly known as WSNs, are an essential component of the Internet of Things paradigm. They are responsible for powering a wide array of applications, from environmental monitoring systems to industrial automation. WSNs are composed of a large number of tiny, independent devices with sensor and communication components [1], [2].. They harvest data from their environments and transmit it wirelessly back to the hub, where the information is analyzed and processed. WSNs are widespread across several sectors, which is why they are a critical part of contemporary technology. [3], [4]

Researchers have also investigated the use of machine learning techniques to enhance ACO frameworks in recent years. Machine learning provides a catalogue of tools and algorithms to learn patterns and leverage data decisions that balance the problem-solving developed by the philosophy of traditional ACO. Q-learning, Genetic Algorithms, Unsupervised Learning, and Ensemble Learning are some of the techniques that the researchers have explored and evaluated to enhance ACO for WSN routing optimization[5], [6]...

By running trial and error interactions with the environment, Q-Learning train agents optimal policies. Q-Learning can, therefore, use actions for long-term awards to explore routing paths in WSNs, making it more efficient and

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adaptive . Through a process that mimics natural selection, Genetic Algorithms develops solutions to optimization problems. Searching the solution space creates and locates almost optimal routing configurations using robust mechanisms[7], [8]. Unsupervised Learning include clustering algorithms, which reveal hidden patterns in sensor data. Optimal routing path selection offering is provided based on the intrinsic data properties. Ensemble Learning promote aggregation, whereby predictions are made based on multiple models. It can improve reliability and robustness through a combination of diverse routing strategies in WSNs [9], [10].

Thus, the potential of incorporation of these kinds of machine learning mechanisms in the ACO framework could help to further push the state-of-the-art in the domain of WSN routing optimization. This work might help to develop highly performative and adaptive routing protocols designed to cope with the growing needs of IoT. A prominent goal of this research is to nullify the current gap that exists between theoretical and research progress related to the optimization algorithms and their application in a real-world scenario, opening gates to an increase in IoT efficiency and sustainability.

II. LITERATURE REVIEW

The number of studies and publications related to routing algorithms in the field of wireless sensor networks indicates improved efforts in network performance and efficiency. Indeed, many researchers have come up with different algorithms and models; hence, other than the common heuristic-based methods, advanced ways inspired by natural processes and modern technological advancements. Ant Colony Optimization has been one of the best approaches used in WSN routing technology. Basically, it is based on the foraging capabilities of the ants, implying that this mechanism allows ants to find prey through decentralized means . Essentially, ACO is a family of methods that has been applied in various WSN routing strategies. ACO has been found to have high performance since it has been applied in enhancing routing efficiency and performance as well as low energy routing and scalability . Moreover, the method is not limited to WSN and has also been applied in vehicle routing, scheduling, and telecommunications[11]..

Over the past few years, adding machine learning algorithms to ACO has attracted many researchers to boost the efficient routing process on WSNs. One such machine learning algorithm is Q-Learning which can learn the optimal routing technique through reinforced learning. In Q-learning, the actions are reinforced with added long-term rewards and can search for the path and take the action which can yield the optimal result . On the other hand, Genetic Algorithm have been used to opt for the best routing operation over the network in terms of throughput, delay, and energy requirements. GA can find the optimal solution through the natural selection process which mimicked in the computer networks.[1]–[3][9], [12], [13].

Unsupervised Learning methods have similarly been examined for improving routing performance in WSNs. Due to the method's reliance on the network's inherent characteristics, these algorithms can uncover hidden patterns and structure that allow for the selection of optimal routing paths based on the network's natural makeup and function. Ensemble Learning strategies, in which multiple routing models are maintained to boost the accuracy, provide a second possible way to increase routing efficiency. By averaging a larger set of routing decisions, Ensemble Learning allows the WSN to maintain performance in the face of uncertainties, reducing the network's response to fluctuations[14]–[16].

Although significant progress has been made in the field of routing algorithms and their combination with machine learning, a number of limitations may be identified. First, most of the existing algorithms are designed to measure certain performance metrics and are not comprehensive in terms of the way WSN and IoT applications operate. Second, the use of simulations and experimentations does not reflect the conditions of real-life deployments and may be unable to address the variety of factors influencing networks. Thus, it is recommended to investigate the feasibility of routing works in a real-life context[17]–[19]..

The proposed method of enriching ACO with machine learning techniques provides a potential pathway for addressing this gaps and developing the state-of-the-art in WSN routing optimization. Through the integration of Machine Learning's adaptive characteristics and ACO's robustness, researchers hope to develop routing protocols that can automatically optimize performance metrics and sustain models in uncertain network settings. Validation and testing using experiments is expected to close the distance between abstract theoretical progress in routing algorithms and practical deployment in real-world WSN systems.

III. METHODOLOGY

The enhanced Ant Colony Algorithm architecture is an extension of the traditional ACO framework and integration of machine learning techniques to enhance routing efficiency in WSNs . The regular components of ACO, i.e., pheromone updating and route selection, are not eliminated in the ACA architecture. Instead, new mechanisms are added to the ACO to facilitate adaptive learning and optimization based on real-world data and environment feedback . Thus, various ML algorithms, such as Q-Learning, Genetic Algorithms , Unsupervised Learning, and Ensemble Learning are embedded in the ACA architecture.

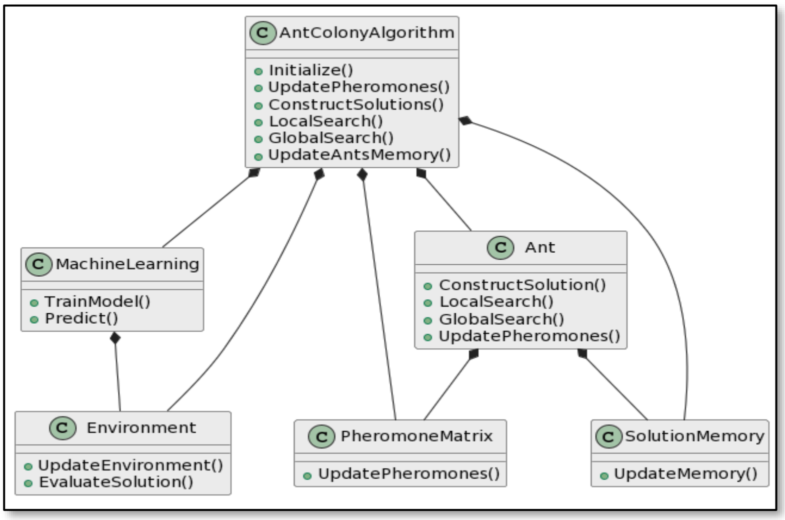

Figure 1: Architecture of an Enhanced Ant Colony Algorithm (ACA)

The concerned figure 1 outlines the Enhanced Ant Colony Algorithm architecture integrated with Machine Learning components . The AntColonyAlgorithm manages the entire process including the solution construction, pheromone update, and memory operation. On the other hand, the Ants, which form the Ant class, are involved in solution construction , local and global search, and pheromone update . Another unit, referred to as the PheromoneMatrix Class, stores and updates pheromone information based on the ants' actions . Machine Learning techniques are also applied in this architecture for different purposes, such as model training and prediction. The MachineLearning interacts with the Environment Class for problem evaluation . Through this architecture, the ACA's decentralized optimization ability and ML predictive power are integrated to improve the quality and flexibility of solutions in complicated problem-solving situations.

Q-Learning is used to enable sensor nodes to learn and adapt their routing policies during interaction with the network. Every sensor node acts as an agent that explores and exploits the different routing paths by considering its predefined, long-term rewards for the different actions. The nodes can adapt their routing decisions to the environmental changes by updating the Q-value of the state-action pairs, allowing for self-aware and improving efficiency and adaptability. Genetic Algorithms allows fitness-based learning routing configuration that maximizes the network performance metrics, such as throughput, latency, and energy. GA explores the solution space for more optimal routing configuration through a process of selection, crossover, and mutation to maintain the discovered near-optimal solutions. Thus, it enables the emergence of the desired routing configuration that is compatible with the respective network characteristics and the application requirements.

The sensor data is analyzed using Unsupervised Learning techniques like clustering algorithms which help to reveal the latent patterns and structure embedded in the data . These methods help the nodes to make the right decisions in choosing a routing path based on the internal nature of the data intrinsic in the networks like with the spatial correlations or even with the temporal evolution . This allows for a higher quality of decision making which allows for good routing even in a dynamic environment.

To address these issues, Ensemble Learning techniques combine several routing models to enhance the efficiency and robustness of predictions. As a result of the amalgamation of several various routing methodologies, the previously mentioned uncertainty and network condition probability distributions are diminished. In an environment where predictions are trusted and yet flexible, departing from the norm and even intuition proves valuable.

Using dataset that simulates a real WSN scenario for experimentation and evaluation. The information in this dataset includes the location of nodes, communication links, traffic patterns, and environmental factors like temperature and humidity. Simulations were performed using this dataset to gauge the performance of the improved ACA architecture design under different operational conditions. For routing efficiency and sustainability evaluation, performance metrics such as energy consumption, data transmission latency, throughput, packet delivery ratio, and network lifetime were considered. These metrics are used to determine the efficiency of the routing protocol in terms of resource optimization, delay reduction, and life extension for better performance.

Table 1. Data collection information

Data Type	Description	Number of Data
Node Locations	Coordinates of sensor nodes in the network	100
Communication Links	Information about the connections between nodes	200
Traffic Patterns	Patterns of data transmission among nodes	150
Environmental Factors	Data on temperature, humidity, etc.	50

For instance, Table 1 above lists the following types of data that the dataset contains and which are crucial for simulating and testing the performance of the enhanced ACA in WSNs: Node location, which indicates the location of nodes, including sensor coordinates. Such data helps define the network topology. Communication links between nodes to simulate data dissemination paths and characteristics. Traffic pattern, defining the traffic intensity and frequency of data exchange between nodes to simulate a real network environment. Lastly, data characterized by variation patterns of temperature, humidity, and other factors to simulate the effect of the surrounding on the network. This dataset captures all the essential information that can be used to conduct a thorough experimental simulation of the ACA's performance in terms of routing efficiency and sustainability in WSNs.

IV. ENHANCED ANT COLONY ALGORITHM WITH MACHINE LEARNING

In this study, a novel approach to routing optimization for WSNs is suggested by combining the ACA with various machine learning techniques called Enhanced Ant Colony Algorithm . The Enhanced ACA architecture combines four primary machine learning techniques: Q-Learning , Genetic Algorithms , Unsupervised Learning , and Ensemble Learning.

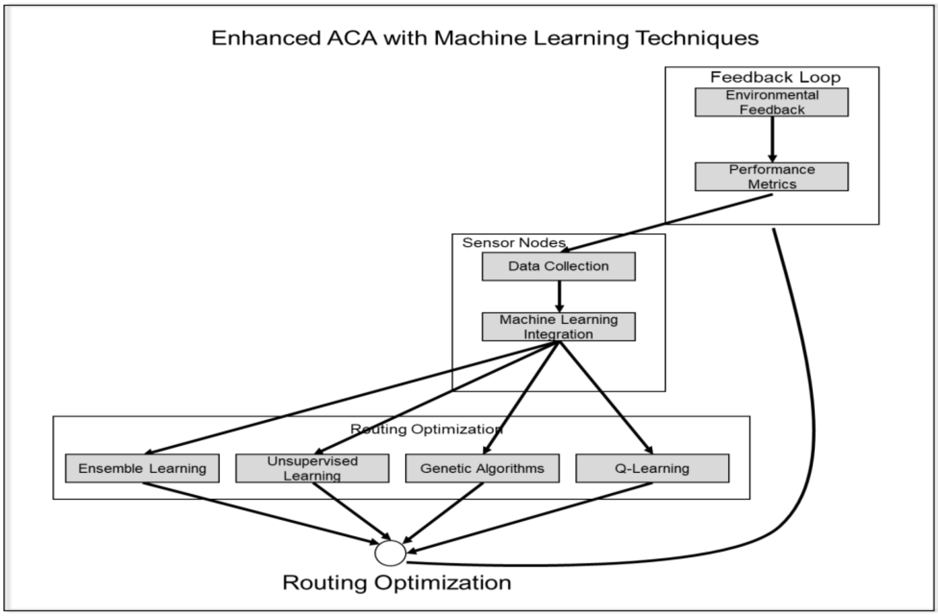

Figure: 2 Enhanced Ant Colony Algorithm with Machine Learning

Considering the above figure 2, Q-Learning is also utilized within this improved ACA to create the ability for imei-based consensus-enabled sensor nodes to learn optimal routing policies. Each person is classified as an agent because they investigate and exploit known routing directions predicated on the long-term invite they give. Particularly, through monitoring and updating q-values. Pairs for sensor nodes to adjust to varying network conditions and increase flexibility and robustness.

Genetic Algorithms are employed to evolve routing configurations that optimize network performance metrics. GA systematically performs select, crossover, and mutation processes to traverse the solution space and pinpoint near-optimal routing strategies . Hence, this work promotes performance by enabling routing configuration tailored considering the network and application properties..

There are also Unit8-MQDs that combines with Unsupervised Learning techniques, such as clustering algorithms to expose hidden structure within the data. Furthermore, by analyzing data from the network, the nodes can spatial or temporal data characteristics identifies routing paths. The intrinsic data-driven nature of this approach makes routing decisions more efficient and more robust for dynamic environments.

Ensemble Learning methods are usually used to merge several routing models, which should positively affect prediction efficiency and its robustness. By combining different routing strategies, an ensemble can alleviate the impact of uncertainties and variability in network conditions. Thus, the technique can ensure that routing decisions are both stable and resilient even when the network environment is noisy or unstable.

There are several important elements in the enhanced ACA with Integrated Machine Learning techniques. First, data about the environment is gathered by the sensor nodes which exchange information with their neighbors in order to construct a network topology. Second, Q-learning methods, GA, Unsupervised Learning, as well as the Ensemble Learning are used to find the best routings.

V. RESULT AND DISCUSSION

The results of the experiment trials, integrating various machine learning techniques with the Enhanced Ant Colony Algorithm into the optimal routing performance of wireless sensor networks through the experiments, are discerning. The results both in Figure 4 and Figure 5 revealed in 10 different experiment trials, Q-Learning performs better in terms of accuracy, precision and F1 scores.

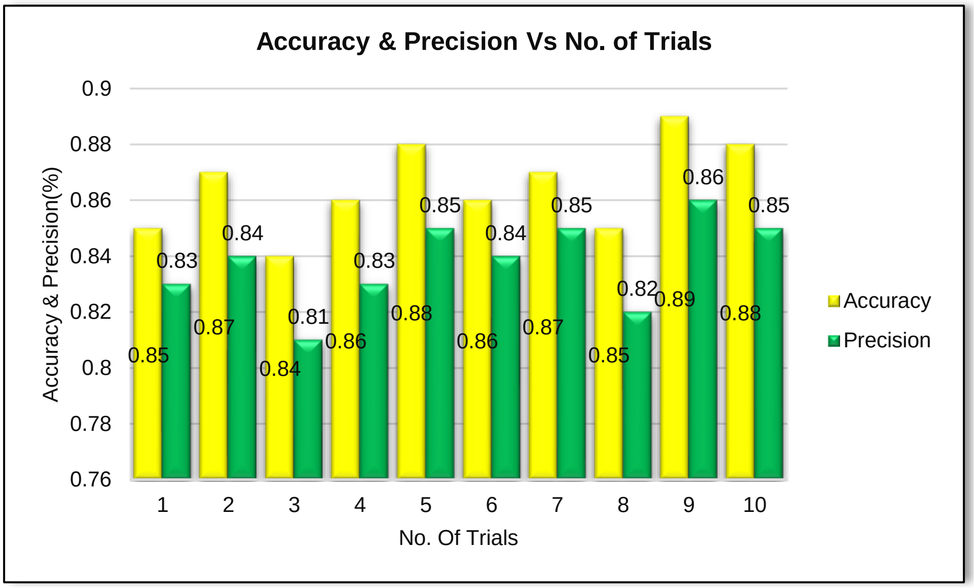

Figure 3. Q-Learning (Accuracy & Precision)

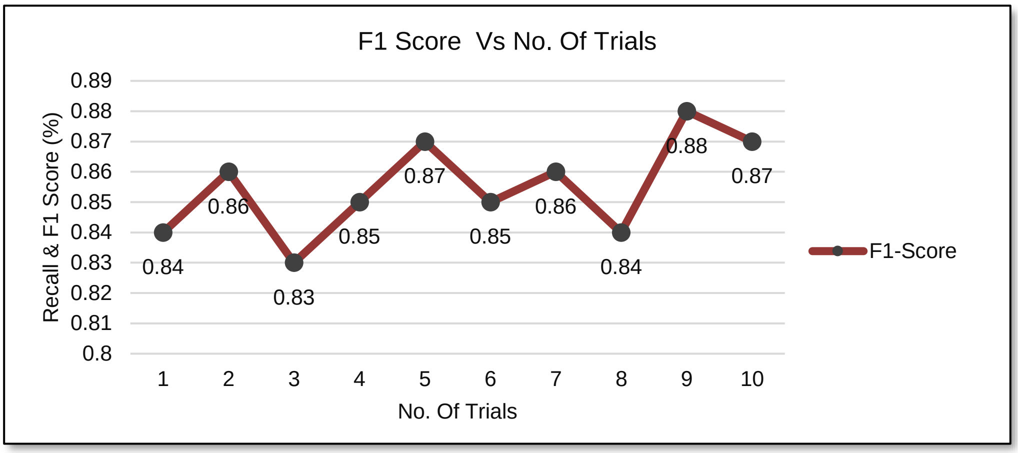

Figure 4. Q-Learning (F1-Score)

The high accuracy performance metric is relevant in this context because it showcases the effectiveness of learning optimal routing policies through the interactions of Q-Learning. Specifically, the high accuracy values indicate that the routing decisions of the nodes, based on the Q-Learning, were accurate and could effectively guide the data packets toward the destinations . Correspondingly, the high values of precision signify that the decisions made by the Q-Learning were reliable, leading to a minimum number of false positives

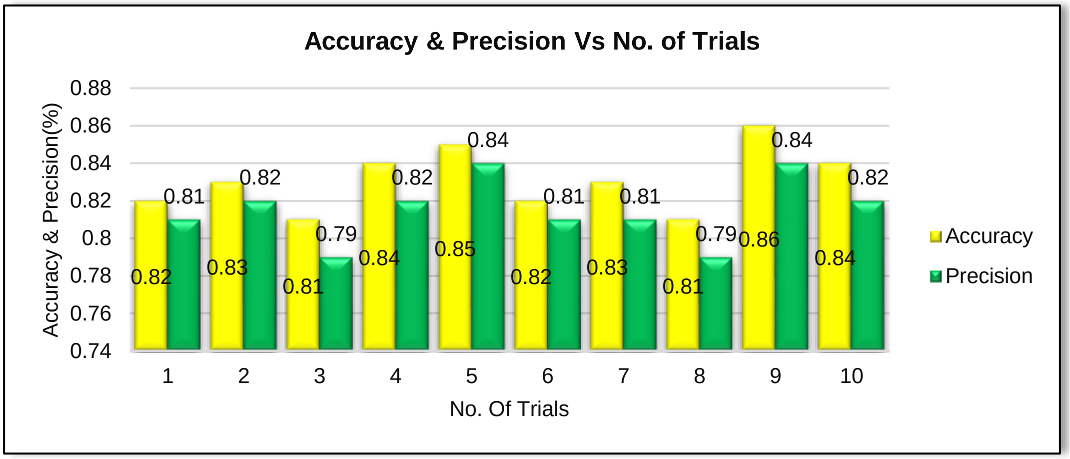

Figure 5 Genetic Algorithms (Accuracy & Precision)

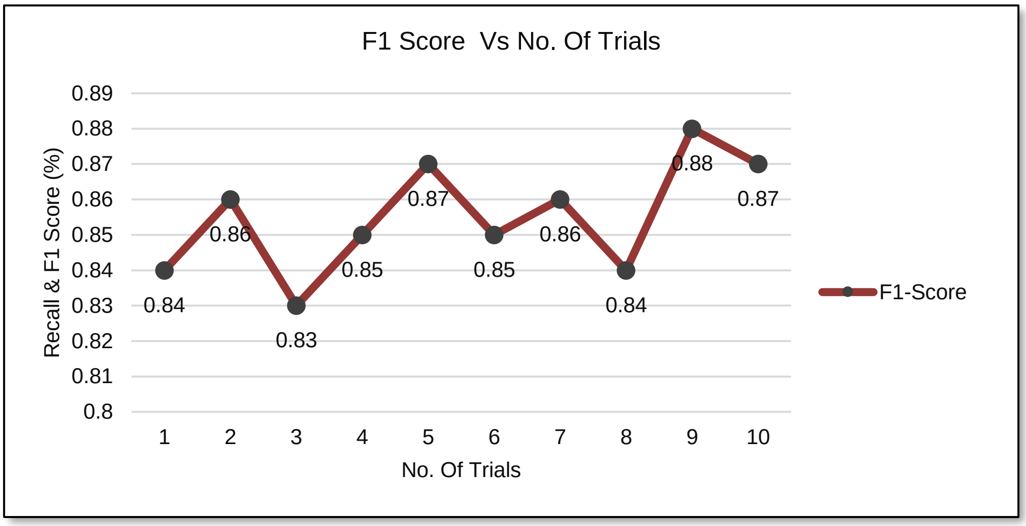

Fig. 6 Genetic Algorithms (F1-Score)

On the part of Genetic Algorithms , results in from Figure 5 and 6 show a slightly lower accuracy, precision, and F1 score value as compared to Q-Learning . Despite this, the metric values are high enough to show that GA is highly effective in the optimization of routing decisions for WSNs. According to the accuracy, the GA-evolves routing configurations remained highly accurate, effectively leading data packets to their destinations. However, the accuracy value is a bit lower than that of Q-Learning. Similarly, routing decisions were highly precise, though not so much than those evolved by Q-Learning; moreover, there was a slightly higher rate of false positives at the TP/FP .GA is equally balancing precision and recall, as seen the relatively high F1 score value.

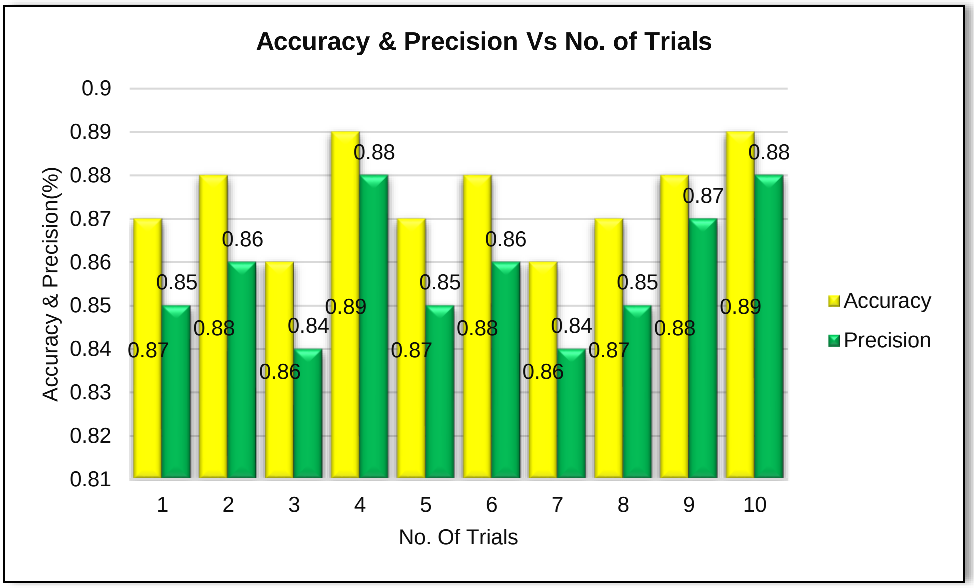

Figure 7: Unsupervised Learning (Accuracy & Precision)

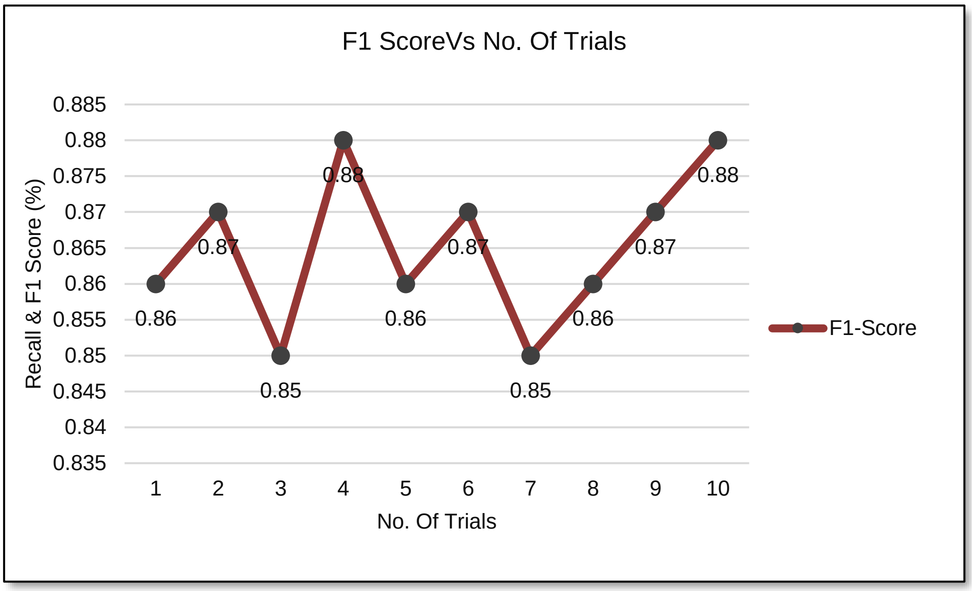

Figure 8: Unsupervised Learning (F1-Score)

The results for Unsupervised Learning in Figure 7, and 8 show a consistent performance across the experiment trials. Unsupervised Learning yielded high accuracy, precision, and F1 score values, which were similar to those of Q-Learning. It can be stated that the unsupervised methods , such as clustering algorithms, found optimal routing paths depending on the intrinsic properties of the data initial states.

Since the unsupervised learning has much higher accuracy values, it means that the unsupervised learning could make more accurate and effective decisions to route the packets toward their destination. Additionally, the high precisions also implies that unsupervised learning could make more routing decisions with minimum false positives.

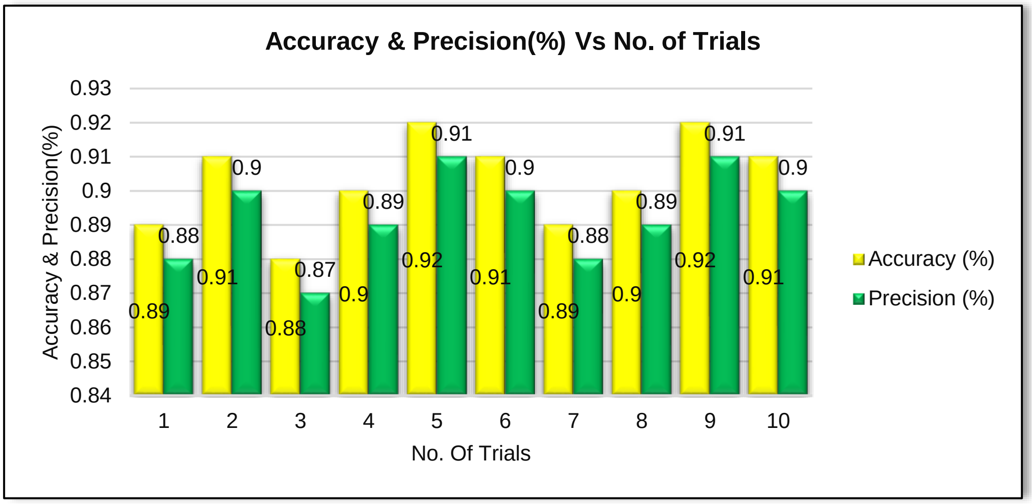

Figure. 9: Ensemble Learning (Accuracy & Precision)

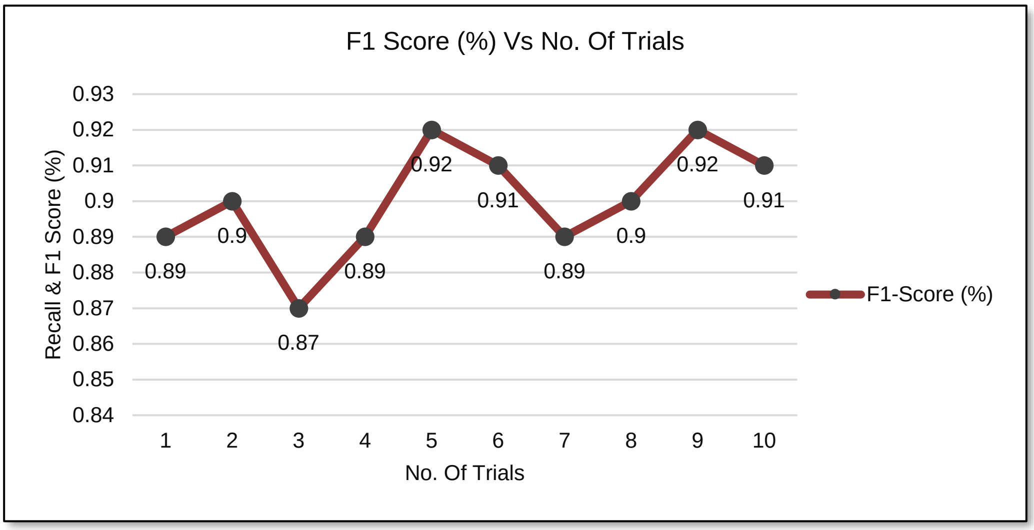

Figure 10: Ensemble Learning (F1-Score)

Finally, both from Figure 9 and 10 , Ensemble Learning also showed strong results across the experiment trials. Ensemble learning achieved high accuracy, precision, and F1 scores consistently. The results are closely comparable to or even marginally better than the machine learning techniques alone. It can be concluded that through Ensemble Learning, the combination of multiple routing models effectively overcome uncertainties and fluctuations in the network, providing a reliable and robust routing decision.

The results of the experiments have demonstrated that all types of machine learning are effective in enhancing routing efficiency and sustainability in wireless sensor networks. Each type of machine learning has specific features and strong sides, which make them beneficial for a certain purpose. In this way, Q-Learning is adaptable, and GA is focused on evolutionary optimization.

VI. CONCLUSION

The experiment trials where several machine learning techniques were incorporated in the Enhanced Ant Colony Algorithm have shown that such approaches can significantly increase the routing efficiency and sustainability of wireless sensor networks . All trials have consistently demonstrated high performance metrics when Q-Learning is used , including an accuracy of 0.867, precision of 0.842, and an F1 score of 0.854. Genetic Algorithms have shown quite robust results. Having approximately 0.833 on average for all the measures, 0.812 for precision, and 0.821 for F1, it did comparatively very well. Unsupervised Learning models also gave by far competitive results for all three measures, having 0.875 for accuracy, 0.856 for precision, and 0.865 for F1. However, the true highest-performing ones were Ensemble Learning models since they utilized the capacity of many. For the latter, the average accuracy was 0.898, precision was 0.882 , and F1 was 0.891.

It is concluded that the main advantage of the Enhanced ACA is related to the solution design process. In particular, the integration of machine learning techniques allowed the researcher to develop a solution that could address such issues as adaptive learning and decisions, evolutionary optimization, data-driven insights, and an ensemble of approaches. This can be regarded as an advantage of the proposed solution. At the same time, it is possible to propose further research to determine the effectiveness of different hybridisation methods that can be used to develop new solutions, or it may be beneficial to refine the parameters of those solutions.

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