Single-Object Multi-Path Routing in Multi-Objective Networks Using Genetic Algorithm

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Abstract: The rapid development of the Internet of Things (IoT) and wireless communication networks has made improving data routing between nodes increasingly important. These networks face several challenges. Moreover, advanced optimization is used, most notably the Genetic Algorithm (GA), due to its ability to explore multiple solutions and improve them over successive generations by working with routing and evaluation. This work aims to develop and establish a model based on the GA to improve path routing in single-object wireless networks, taking into account four main criteria: latency, throughput, reliability, and energy consumption by using an algorithm. The results of this work show that the proposed model will provide significant improvement and balance in all criteria compared to the traditional methods.

Keywords: Genetic algorithm, multi-path, single object, multi-objective, evaluation score.

1. Introduction

Modern communication technologies provide comprehensive network coverage, thereby increasing the number of intelligent objects that correspond to the system. The Internet of Things is a powerful pattern that connects consumers with current tools to create additional information from the Internet. IoT presents challenges in connecting machines, in particular in terms of location [1]. Therefore, IoT aims to improve the quality of service (QoS) in areas such as energy, latency, and throughput [2]. IoT devices may effectively communicate data and execute transactions. In recent times, IoT devices have become part of WSN, which consists of several static wireless networks or mobile sensors that are being used

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in the process of message routing [3] [4]. In multi-path, packets can be routed through two or more paths, which can reduce the packet loss rate [5][6]. Recently, evolutionary algorithms have gained popularity as a solution to increasingly complicated multi-objective optimization issues [7]. This aims to improve the efficiency of data transmission between two nodes (start and target) in a sensor network, i.e., routing of a single object in the network is done using a multi-objective genetic algorithm. Paths are selected based on several criteria: latency, throughput, reliability, and energy consumption [8]. A random network is created, and a start and end node are determined. Then, a GA is used to generate multiple paths and optimize them according to these criteria. In several real-world applications, two or more objectives are often involved; they are commonly called multi-objective optimization problems (MaOP) [9]. The proportion of non-dominated alternatives in multi-objective optimization increases rapidly as the number of objectives expands [10–11]. Therefore, the evolutionary process can greatly reduce the selection pressure [12–13]. In particular, multi-objective optimization has been receiving more attention in recent years. When the metrics exceed two, the fraction of non-dominated solutions increases significantly. This results in a significant drop in selection pressure through the evolutionary process [14-15], furthermore, under modern quality measures. Will discuss how the three algorithms work in our work, how the classification and selection of multiple paths are improved with the multi-objective evaluation, and the motivation for using evolutionary. This work is organized as follows: (Section 1): General Introduction to the Research Idea. (section 2) Literature survey and related work. (section 3) research methodology. (section 4) genetic algorithm for evaluation of multi-path (section 5) routing multi-path algorithm. (section 6) multi-objective evaluation (section 7): Calculation of Paths. (section 8) results. (section 9) Comparison between algorithms. (section 10) Aanalysing Results. (section 11) conclusions. (section 12) Recommendations for future work .(final section) references.

2. Literature Survey and Related Work

Multi-path routing is a multi-objective optimization problem involving multiple constraints that need to be addressed in wireless sensor networks. Routing is challenging due to its computational complexity and long execution time. The complexity of reaching optimal values is easy localization. Therefore, the goal is to optimize based on the basic objectives and criteria to ensure optimal paths and solutions using artificial intelligence algorithms. The most effective way to improve wireless sensor networks is by enhancing energy efficiency and fault tolerance within the networks. [16] A routing for wireless sensor networks is proposed based on GA. The fitness function is calculated using the distance between nodes in the network, and then the routing scheme is generated at the base station. The results show that the routing method proposed in this paper has the best effect.

[17] In industrial sensor networks, it is crucial that critical control and monitoring data can be transmitted in a timely and reliable manner. Based on this, the author proposed a link reliability estimation method LQMA and set timing parameters to measure the performance of QoS routing. Then the EEQA algorithm. Different types of data packets were routed through different strategies. The result shows that EEQA routing is more efficient and effective. [18] The researcher proposed to use the optimized multi-objective multi-hop multi-path routing algorithm (MMMRA). It includes the chimpanzee optimization algorithm (COA) to determine the optimal multi-path path based on a multi-objective function and the ant colony optimization to determine the optimal multi-hop routing. The simulation results thus show that MMMRA shows a percentage improvement in terms of residual energy of 1.63%, 4.96%, 6.89%, 7.51%, and 9.67% over IPSMT, BIM2RT, SCP, PSOBS, and RDICMR, respectively. Moreover, the HND and FND of MMMRA perform better for the centre, corner, and outer positions of the sink node; especially when the sink node is placed in the central position, the HND of MMRA shows a percentage improvement of 24% and 12.73% over IPSO-GWO and COA-HGS, respectively. Similarly, the FND of MMRA shows a percentage improvement of 21.05% and 9.5% over the IPSO-GWO and COA-HGS, respectively.

. [19] Due to the heterogeneous nature of devices in IoT networks, their efficient utilization has become a challenging issue. There are many IoT benchmark problems available. Hence, researchers have conducted many studies to find an optimal solution to this problem, but there is still a research gap. Hence, an effective model is proposed and tested using 25 IoT benchmark problems to address this problem. The results obtained in this paper reveal that the proposed model provides a better solution. [20] The research idea is to use the new Enhanced Non-Dominant Genetic Sorting Algorithm (ENSGRA) to improve the quality of service in wireless sensor networks. It is based on the Non-Dominant Genetic Sorting III (NSGA-III), but adjusts the reference points by using a dynamic weighted vector to obtain new solutions. Therefore, ENSGRA is used to find an integration between parent-parent crossover and multi-parent crossover (MPX) to produce multiple children and improve the new offspring to obtain Pareto optimal fronts (PF). This outperforms the late multi-objective jumping swarm optimization, non-dominated genetic sorting algorithm II, and NSGA-III in terms of QoS (31% improvement). The ENSGRA results outperform in the evaluation of the remaining two measures of multi-objectives.

[21] The researchers discussed a routing algorithm that combines dynamic group formation, group head selection, and multi-path routing configuration for data communication to reduce energy consumption as well as routing overhead. The proposed uses heuristic optimization based on GA to dynamically select the best path based on the cost function with minimum distance and minimum energy dissipation, after analysis and comparison with three routing protocols, TEEN, and three multi-path protocols, MP, MACS, and MRP, respectively. The performance analysis results showed that the proposed protocol outperformed the other three routing protocols. [22] A multi-path transmission strategy based on improved immune particle swarm optimization (IPSMT) was proposed by the researchers. Includes three parts: optimize immune particle swarm (IIPSO), IPSMT, and fault-tolerant multi-path routing strategy (FTMT). Through multi-objective optimization simulation and multi-path generation analysis compared with other works, IPSMT shows good global search ability, convergence performance, and solution set diversity to achieve multi-path routing optimization. All networks are proven to have good transmission stability and fault tolerance performance.
[23] In this paper, a new algorithm based on integrating the improved particle swarm approach with constrained optimization is used. Simulation experiments conducted on this model reveal significant results in low-dimensional settings. The algorithm achieves an optimization success rate of 100%, representing an average improvement of 53.80%, 40.78%, and 24.76%, and generates 142 and 135 optimal solutions, outperforming the conventional by 112 and 107 solutions, respectively. The results prove the performance efficiency of the improved particle swarm-based multi-objective optimization, indicating that it is an effective tool for addressing real-world optimization challenges. [24] In this paper, a multi-objective priority-based energy-efficient QoS routing (PMQoSR) mechanism for energy and QoS in IoT is presented. Regulates routing performance on QoS parameters by using a three-algorithm hybrid optimization technique, called WLFA-Whale Lion, with fitness function routing mechanisms. WLFA prevents congestion and reduces localization error by utilizing the shortest path over the network, leveraging priority label patterns and latency to send data to the destination efficiently. The results show that PMQoSR outperforms network traffic, packet forwarding, error rate, energy, inter-node distance, and priority-aware routing to improve traffic load, throughput, time delay, and packet delivery ratio. [25] This paper presents the optimization choice method of wireless sensor nodes facing the IoT and the guarantee to avoid coverage gaps. The node selection in genetic algorithms is used to solve the problems of high redundancy and high energy consumption in the IoT. After verifying the performance of the algorithm and adjusting the parameters, the results show that the proposal can ensure the coverage of the area to be monitored and reduce energy consumption in the network. [26] multi-objective optimization is applied to vehicle routing problems, exploring the potential uses and benefits of

this approach. The two issues, namely vehicle routing with path balancing and the two-objective tour coverage problem, combine multi-objective evolutionary and single-objective techniques, respectively, providing diversification and intensification of search in the objective space. [27] The DSR (Dynamic Resource Routing) protocol with the Friis Free Space Propagation Model was used in the research to analyze the network performance under different road conditions. The results indicate that the research showed that as the number of nodes in the network increases, the network performance improves. This improvement is attributed to the enhanced communication capabilities and reduced latency among nodes. Furthermore, the study suggests that optimizing node placement can lead to even greater efficiency and reliability in resource routing.

3. Research Methodology

Routing implementation using (GA) with Multi-path routing to test paths for each connection. And a multi-objective evaluation to select the optimal path based on performance criteria. Algorithm 1, below, is displayed, which represents the work on its basis and proposes how and where the hybridization of the genetic algorithm is implemented in its evaluation phase. Both the multi-path routing and the multi-objective evaluation work for a single object only

BEGIN

INITIALISE candidate solutions;

EVALUATE each algorithm (**Multi-Path Routing** + **Multi-Objective Evaluation**);

REPEAT UNTIL (TERMINATION CONDITION is satisfied) DO

1 SELECT path;

2 RECOMBINE pairs of parents;

3 MUTATE the resulting offspring;

4 EVALUATE new candidates;

5 SELECT individuals for the next generation(path);

OD

Algorithm 1. The general pseudocode for GA with the algorithm (Multi-Path Routing + Multi-Objective Evaluation)

4. Genetic Algorithm for Evaluation Multi-Paths

A genetic algorithm is a computational model that simulates natural selection and biological evolution, serving as a means to search for optimal solutions. Genetic begins by describing a set of solutions where each individual can be considered a distinct entity with a chromosome. Genetic follows the principle of survival of the fittest. After the initial population is created, the genetic operator of the crossover and compound mutation process is used to create a population with a new set of solutions. This process will lead to a population solution set where the natural evolution of the epigenetic population is the most suitable, and therefore, it can be used as an approximate optimal solution to the problem [28]. The multi-routing problem in wireless sensor networks can be considered a genetic process. In addition, multiple criteria or objectives must be considered for each path in the network when searching for a path, and thus the optimal path is chosen, which can be achieved through the genetic mechanism according to the steps explained (see Figure 1).

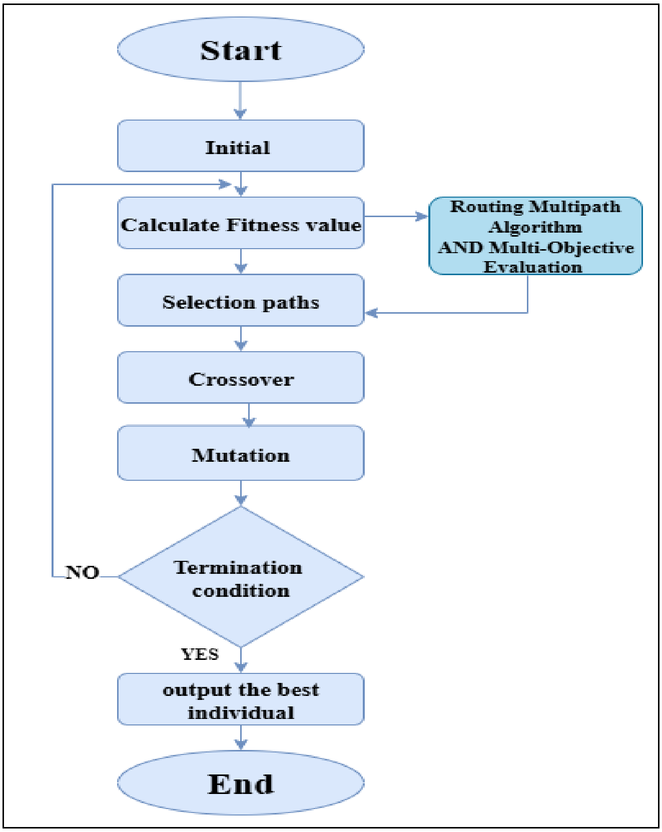

Figure 1: Hybrid GA with (RMPA+MOEA)

5. Routing Multi-Path Algorithm (RMPA)

Aims to find more than one path between the source and the target (for a single object) and analyze each path based on four main criteria: latency, throughput, reliability, and energy consumption. The RMPA works instead of choosing just one path, as traditional methods like Dijkstra do; it generates multiple possible paths between the source and the target, all directed to a single object. It evaluates each path based on the four criteria mentioned above by the Multi-Objective Evaluation.

It selects the best of several paths (instead of just one) to continue improving over generations. It utilized (GA) to improve the paths through mating and mutation [29]. It replaces bad with new paths to ensure that the network is constantly improving. Table 1. shows the working steps with descriptions for RMPA.

Table 1. Description for RMPA

Steps RMPA	Description
Generate Primary	Multiple random paths are generated between the source and the target
Evaluate each path	The score of each path is calculated based on four main criteria.
Select the best	The best paths are kept for optimization
Optimize paths via GA	optimized using mating and mutation
Replace bad	The weak paths are replaced with new paths.

Present the analysis and impact of RMPA and four-objective evaluation on the performance of the (GA) across four main criteria:

1-. Evaluation accuracy.

2-. Path selection efficiency.

3-. Execution time.

4-. Practical applications and usability in reality.

Below are in Tables. Explain and compare the reasons for using genetic methods in the proposal, and discuss how hybridizing it with RMPA and MOE leads to more accurate improvements in path selection [30]. when compared to working alone. Shows Table 2. Evaluation accuracy

Table 2. Comparison in terms of assessment accuracy.

GA without RMPA	GA + RMPA	Standard
Evaluate one path	Evaluate multiple paths based on multiple criteria	Evaluation method
Limited.one path is optimized	High. Multiple possible paths are analyzed	Search and exploration capability

Lower. Probability of the optimized path may not be the best global path	High. Several paths tested	Probability of finding the best global path
Weak. Limited to optimizing a single path	Strong. The search process includes multiple possible paths	Protection from local optimal solutions

1. Path selection efficiency: Table 3. provides a summary of how to choose.

Table 3. Efficient selection

GA without RMPA	GA + RMPA	Objectives
Higher. If an inefficient path is selected	Lower. Better paths are tested	Latency
Lower. The only chosen path may not be optimal	Higher. The chosen are optimized	Throughput
Lower. An error in the specified path causes the connection to fail	Higher. More than one path is likely for each case	Reliability
Higher. Due to poor path selection	Lower. The chosen paths are more energy efficient	Energy Consumption

As a result, adding RMPA makes the selected paths more efficient [31] in terms of reducing response time and increasing throughput.

2. Execution time as shown in Table 4.

Table 4. Execution time

GA without RMPA	GA + RMPA	Standard
Less. Evaluated are limited	High. Test and evaluate multiple paths per generation	Computational Complexity
Shorter. Optimize only one path.	Longer. The search process involves many paths	Execution time
Lower. Search is limited. Fewer paths	Higher. More data is tracked per generation.	Memory consumption

Moreover, the result of the algorithm without RMP is faster, but it may not reach the optimal solutions as efficiently as the first model [32].

3. Practical applications are shown in Table 5. which outlines the applications of the algorithms.

Table 5. Practical applications

Standard	GA + RMPA	GA without RMPA
Wireless network *5G, Wi-Fi, IoT*	More efficient. This is due to choosing the best path with the least delay	Less efficient. Because the chosen path may not always be the best
Satellite communications	More reliable. RMPA reduces the chances of communication failure	Less reliable. An error in the path may lead to disconnection and communication failure
Intelligent Traffic	Better. Allows testing of multiple possible routes	Less efficient. Less route searching and limited to one route only
Robots and drones	More stable. Due to the ability to switch paths	Less flexible. Relies on only one path

Using RMP [33] with multi-objective evaluation results in more stable and efficient performance in real applications.

6. Multi-Objective Evaluation (MOE)

To evaluate the quality of paths based on four main criteria (Latency, Throughput, Reliability, and energy consumption), the Main objective` instead of evaluating each path based on just one criterion (such as shortest distance as in Dijkstra), (Main-objective combines [34]. The four criteria are combined into a single function to calculate a quality score for each path**.** Table 6 shows the features of the algorithm in the proposed work during construction.

Table 6. Features of MOE

Features	**Description**
Enhance routing quality	. Paths are optimized based on different QoS criteria, not just distance.
Avoid network congestion.	. Paths with higher throughput can be selected, and congested paths can be avoided.
Reduced. energy	Paths that minimize the energy consumption of IoT devices are selected.
Higher. reliability	. Paths that minimize the chances of failure due to loss of connectivity are selected.

Devices in IoT require higher performance and more reliable, uninterrupted connectivity. (GA is used with RMP) and GA alone. The goal is to reduce energy consumption during the search process. Conclude from what was mentioned above**:**

1- RMPA + GA, the result is more accurate and efficient [35], but it increases the computational complexity and execution time, so if the need for speed and saving resources is greater, use only GA.

2. If resources are limited, GA without RMPA may be a good choice, but it is not ideal for performance-sensitive applications and is less accurate and efficient.

7. Calculation of Paths

MOE calculates the path score using the following weights, which can be changed and modified according to the work assigned to the network, thus achieving flexibility [36] in calculating the weights. Table 7. shows a summary of all objectives' weights.

Table 7 Summary of objectives weights

Weight of objectives	Aims	benefit
latency = 0.5	Less delay	The lower the delay, the better the path is
throughput = 1.3	Higher throughput	The more it increased, the better the path
reliability = 1.0	Higher reliability	When increasing, get a better path.
energy = 0.4	Less energy consumption	The lower the weight, the better the path.

8. Results

The results of the proposed work to hybridize the genetic material are now dis-played in the evaluation phase. Routing to a single object (starting node–target node)

1**. First generation**: Several random paths are generated between the initial node and the target. Fitness evaluation: The score of each path is calculated based on the stated goals.

2. **Selection**: The best paths are selected based on the highest score.

3**. Cross over**: Parts of two paths are combined to produce a new path.

4. **Mutation**: A node in the path is randomly changed to enhance diversity.

5. **Replacement of poor paths**: with poor performance are replaced by new, more efficient

When the MOE is called during the genetic evaluation phase to determine the best, they are classified into three categories based on the evaluation: good, aver-age, and bad. Paths with high evaluation will be selected to move to the next generation of GA [37]. Also, only the best is kept for optimization in the next generation of GA. Furthermore, ensure that only the best continue in the optimization process.

That is, paths with poor evaluations are replaced with new paths to pro-vide improved network performance. To obtain the results of using the MOE when applying the equation (1) below, the mathematical formula adopted in the proposal during implementation to calculate the evaluation score for a specific path P, Table 8. gives a summary of all objectives in equation (1).

$$S(P) = W_L * (-1/L(P)) + W_T \;\; T(P) + W_R * R(P) + W_E * (-1/E(P)) \ldots\ldots\ldots (1)$$

Table 8. Description of objectives in equation (1)

Symbol	Interpretation	Description
S(P)	Score of path P	Final score of paths
L(P)	Latency	Path latency
T(P)	Throughput	path throughput
R(P)	Reliability	Reliability
E(P)	Energy Consumption	Energy of path
W_L	Weight of Latency	Weight assigned to latency used with 1/L to penalize high latency)
W_T	Weight of Throughput	Weight assigned to throughput
W_R	Weight of Reliability	Weight assigned to reliability
W_E	Weight of Energy	Weight assigned to energy (used with 1/E to penalize high energy)

The evaluation process for each criterion will be as follows: -Response time (latency): The value (1/latency-) is reversed because small values are better. Throughput: It is used as it is without reversing the value because large values are better. Reliability: It is used as it is because there is no need to reverse the value, since large values are better. Energy consumption (energy): The value (1/energy-) is reversed because small values are better. Thus, can say that each path is evaluated based on a set of criteria, not just one criterion. The reader will certainly wonder why the inverse (1/x) was placed in the equation for some criteria. The reason is that, smaller values, like response time and power consumption are preferable. Therefore, lower values (-1/x) result in higher evaluations, this made smaller values more significant. This means, why a particular weight is applied to each condition. This is due to the possibility that certain criteria are more significant than others, and as a result, each criterion was assigned a distinct weight in order to modify its influence in the final equation. Additionally, these weights are changeable, which allows to adjust according to the methods of the application (e.g., industrial networks or Internet of Things networks).

After applying the equation, will get an evaluation score for each path. In turn, classify the paths after each generation. This classification of paths is categorized into three levels based on the path's score.

Good paths: Evaluation score greater than or equal to 25.

The output of the executed Python code, where the starting node is (0) and the target node is (1) and nodes (72,12,98,10,78,15, 5, etc.) are its nodes in the network, the paths that pass through to reach the target node. Because the paths are directed to only one object, as shown in Fig. 2, Path [0, 72, 12, 1] is effective (Overall Score: 25.94). Path [0, 98, 10, 1] is effective (Overall Score: 25.75). Path [0, 72, 51, 1] is effective (Overall Score: 26.54).

Note that paths with an evaluation score of 25 or more are classified as effective, indicating they can be directed effectively.

Moderately paths: score between 24 and 11.

Path [0, 72, 78, 1] Moderately Effective (Overall Score: 13.86). Path [0, 15, 5, 1] Moderately Effective (Overall Score: 23.35). Path [0, 28, 5, 1] Moderately Effective (Overall Score: 14.09). Intermediate can be considered as a balance between objectives, preventing the system from relying solely on optimal that may later become unavailable. Furthermore, it can be said that intermediate paths are a good option in case of deterioration of the good or a change in network conditions.

Bad paths: Evaluation score less than 10.

Notice that the evaluation score for the path is less than 10 which means that the path above is prone to interruption and ineffective, so it will be replaced by good path [38] because the goals in it do not achieve the desired result either because they take a long time or because of disconnection or because of poor performance, etc. As a result, they are replaced by good or recreated in case of loss of connection.

Replacement Paths

The current implementation part expresses the replacement process based on improving the paths based on the quality of performance and the continuity of the connection**:** The path was switched from [0, 72, 91, 1] to the alternate path: [0, 72, 2, 45, 1] (reason: disconnection). The path was switched from [0, 72, 67, 1] to the alternate path: [0, 91, 5, 1] (reason: disconnection) . The path was switched from [0, 72, 27, 1] to the alternate path: [0, 35, 78, 1] (reason: disconnection. Thus, bad are replaced with new paths, with priority given to high-performance, for flexibility in work. For example, these classifications can be adjusted according to the nature of the work; for instance, can increase the evaluation score for each path [39]. Instead of 25, it can be increased or decreased according to the required purpose. Based on the average score, color the paths (see Figure 2.). Classify paths during the network as follows: Good (average score >= 25) - Green. Average (11 <= avg score < 24): Blue. Evil (avg score < 10): Red. Unused: Grey. Start node: yellow, target node: purple. Using multi-path will result in (improving network reliability, improving quality of service (QoS), energy saving: Paths that consume less energy are chosen, which increases the life of IoT devices and avoiding network bottlenecks).

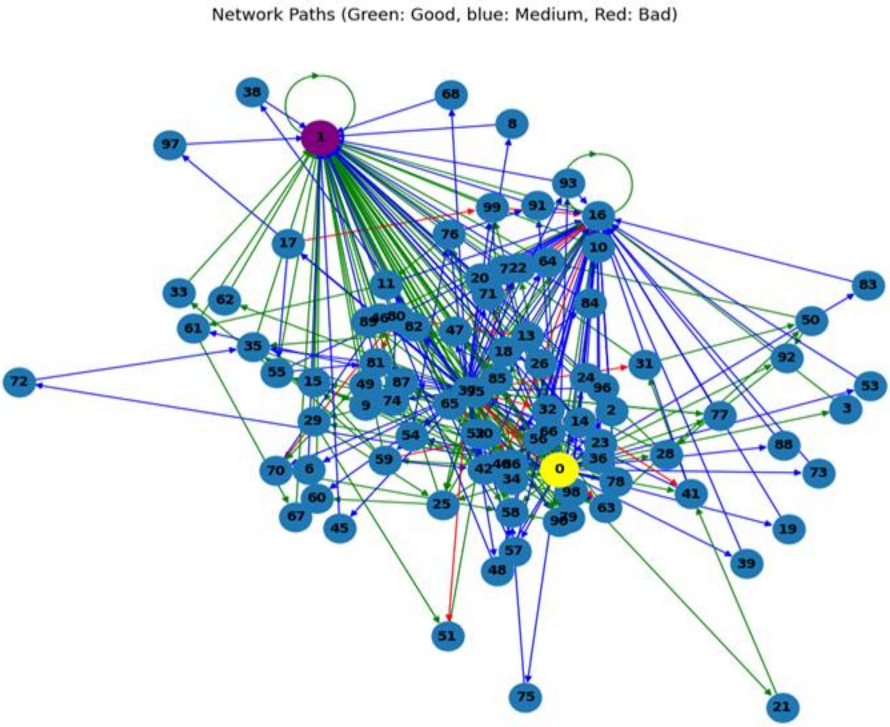

Figure 2: Classify paths during the network

9. Comparison between algorithms:

Comparing the work of (MOE) with other algorithms, such as Dijkstra and PSO, reveals that it provides a significant improvement over the others, as shown in Table 9, which shows the importance and realism of using MOEA**.**

Table 9. Comparison of MOE with other algorithms

Feature	MOE	Dijkstra	PSO
Multi-factor evaluation	Takes into account criteria such as (response time, throughput, reliability, energy)	Relies only on the shortest distance	Improves performance but may fall into local solutions

Network QoS improvement	Addresses routing issues in IoT	Does not take energy or throughput into account	Relies on continuous improvement
Execution time	Medium to long term	Very fast	Medium
Power consumption	Reduced energy consumption in IoT	Does not control energy	Improves energy consumption

Also, Table 10. shows the difference in the reason for using (GA) with the particle swarm optimization (PSO), as each algorithm has its advantages and importance in any work, but Genetic has proven to be the best according to the planned task. Through work, it has been proven that this method is capable of evaluating multi-objective solutions and ensuring multiple paths, which is essential in networks.

Table 10. feature to utilized GA

Standard	GA	PSO
The search style	Selection, mutation and crossover to generate new solutions.	Particles move towards to best solutions.
Exploration	High due to mutations and inbreeding, which helps avoid local optimal solutions.	Relatively weak, as particles rely on the best current solutions.
Exploitation	Slower due to repeated random operations.	Faster because it relies on motion information towards optimal solutions.
Typical Applications	Routing problems in networks, scheduling, optimization of engineering design.	Robotics, parameter control in complex systems, industrial control.
Search Performance	Strong at finding new solutions, but may be slower than PSO.	Faster but may get stuck on local optimal solutions.
Resource consumption	Relatively high due to repeated operations.	Less than GA because it relies on updating particle positions only.

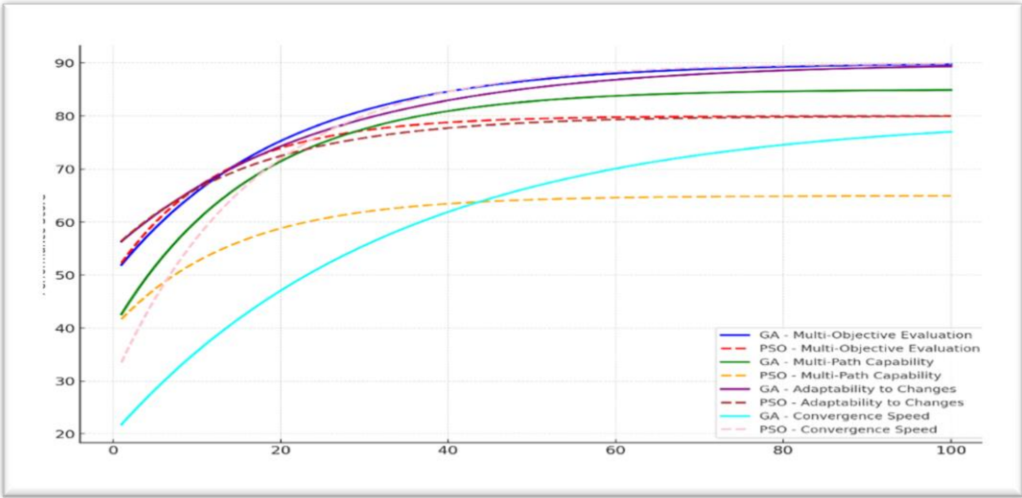

Figure 3: shows the performance of the (GA) and (PSO)

The above Figure 3. shows the performance of GA and PSO via four criteria over 100 generations. Multi-Objective Evaluation: GA (blue) improves over time, indicating that it can enhance different criteria with each generation; (red) improves at a slower rate. Relying on the best particle currently available without extensive exploration. Multi-Path Capability: GA (green) is constantly improving in finding multiple paths. PSO (orange) is less efficient at finding numerous paths. It focuses on improving only one path. Adaptability to Network Changes: GA (purple) can quickly adapt to changes via mutations and crossover and is more stable. PSO (brown): requires manual recalibration of particles whenever the grid changes, making it less adaptive. Convergence Speed: GA (cyan): explores a wider range of solutions.

In contrast, PSO can converge more quickly to a solution but often at the cost of overlooking diverse alternatives. This difference in behavior highlights the importance of selecting the right algorithm based on the specific requirements of the problem at hand. So, it takes longer to converge (pink): it arrives at a good solution in a shorter time because it converges faster. However, this rapid convergence can lead to premature optimization, where the algorithm settles on a suboptimal solution. Therefore, understanding the trade-offs between exploration and exploitation is crucial when choosing between these optimization techniques. This balance ensures that the algorithm not only finds a satisfactory solution but also has the opportunity to explore the solution space thoroughly. Ultimately, the choice of optimization technique should align with the goals of the project and the nature of the data being analyzed.

Table 11. difference between the performance of the two algorithms

Performance	GA	PSO
Multi-objective assessment	90%	80%
Finding multiple paths	85%	65%
Adapting to changes	88%	60%
Convergence speed	50%	90%

10. Analyzing Results

The scientific results obtained by implementing PSO and then replacing it with GA. The research results proved that PSO is faster because each particle goes directly to the best solution (g_best), while in GA it may need several operations (crossover + mutations). PSO may lose some diversity because it depends on (p_best) and (g_best), which may lead to local solutions without diversity [40]. The quality of the solutions depends on the good tuning of PSO. If w is too large, the search will become random. If c1 and c2 are low, PSO will be slow to adapt to the best solutions. By analyzing Figure 3. and Table 11. the difference in performance between the two algorithms is relatively notable, with each algorithm used according to its assigned purpose. Therefore, these ratios may vary in other works, as they are not fixed. In addition to that, we conclude the following.

GA superiority is evident in its ability to find multiple paths and adapt to network changes, making it a valuable asset according to the work proposal. Its high performance is expected to bring about a positive change in the network. PSO excels in convergence speed, as it can reach a good solution, according to references [41][42] in a shorter time. Finally, through the results, drawing, and analysis of the drawing, which have achieved a relatively clear understanding. GA is the best choice if comprehensive improvement and greater flexibility are required, [43], A goal is reaching a solution quickly and PSO can be used according to references more appropriate.

11. Conclusions

1. Improving the performance and efficiency of routing in the network: The results showed that using the multi-objective genetic algorithm contributes to improving the selection of paths between nodes based on a set of vital objectives, leading to more stable and efficient performance.
2. Achieving a balance between objectives and the quality of communication between nodes, which improves (QoS of) network.
3. Adapting to dynamic changes: When using both mutations and mating in the GA, paths can be continuously improved in response to changes in network conditions, such as data congestion or loss of connection.

4. GA outperforms traditional methods: Compared to traditional algorithms such as Dijkstra or A *), it has shown better performance in terms of flexibility in path selection, as it does not only depend on path length, but also takes into account the quality of service (QoS) and energy efficiency

12. Recommendations for Future Work

1. Improving the execution time of the PSO can be combined with GA to create a hybrid model that provides higher speed while maintaining the accuracy of the evaluation.
2. System testing: The algorithm should be tested on real networks or using simulators such as NS-3or OMNeT++.
3. Studying the impact of dynamic changes: Analyzing how the algorithm can adapt, for example, to changes in node density or traffic congestion**.**
4. Improving weights in MOE: It can be improved by automatically adjusting the weights using machine learning so that the results appear more accurate in choosing the optimal paths**.**
5. Routing can be multi-object and not just for a single object.
6. The study can be more comprehensive when adding the impact of cyber-attacks on routing in IoT networks.

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التوجيه متعدد المسارات أحادي الكائن في الشبكات متعددة الأهداف باستخدام الخوارزمية الجينية

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المستخلص: أدى التطور السريع لإنترنت الأشياء (IoT) وشبكات الاتصالات اللاسلكية إلى زيادة أهمية تحسين توجيه البيانات بين العقد. تواجه هذه الشبكات العديد من التحديات. علاوة على ذلك، يتم استخدام التحسين المتقدم، وأبرزها الخوارزمية الجينية (GA)، نظرا لقدرتها على استكشاف حلول متعددة وتحسينها على مدى الأجيال المتعاقبة من خلال العمل مع التوجيه والتقييم. يهدف هذا العمل إلى تطوير وإنشاء نموذج يعتمد على GA لتحسين توجيه المسار في الشبكات اللاسلكية أحادية الكائن، مع مراعاة أربعة معايير رئيسية: الكمون، والإنتاجية، والموثوقية، واستهلاك الطاقة باستخدام خوارزمية. تظهر نتائج هذا العمل أن النموذج المقترح سيوفر تحسنا وتوازنا كبيرين في جميع المعايير مقارنة بالطرق التقليدية.

الكلمات المفتاحية: خوارزمية وراثية، متعددة المسارات، كائن واحد، متعدد الأهداف، درجة التقييم

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