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# Genetic Algorithm based Routing in Wireless Sensor Networks with Various Distance Metrics

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**ABSTRACT** The study highlights the operational characteristics of wireless sensor networks (WSNs). It describes genetic operators and parameters that serve as the foundation for the genetic algorithm's functionality. The optimal values for population size and the number of generations required for data routing in WSNs were determined. The mathematical framework and application aspects of distance metrics such as Euclidean, Chebyshev, Manhattan, and Minkowski were analyzed. A block diagram of the proposed genetic algorithm for data transmission between sensor nodes is presented. The effectiveness of the developed genetic algorithm was investigated for route formation using different distance metrics in a network with nodes characterized by three operational radii. Experimental results indicate that, for finding the shortest route with minimal computational time in a network of 25 sensor nodes, the optimal genetic algorithm parameters are 150 generations and a population size of 300. Simulation results demonstrate the superiority of the proposed solution over the greedy algorithm in terms of route length.

**KEYWORDS** routing; genetic algorithm; wireless sensor network; greedy algorithm; Euclidean metric; Chebyshev metric; Manhattan metric; Minkowski metric.

## I. INTRODUCTION

The use of wireless sensor networks (WSNs) is rapidly expanding across multiple domains, including environmental monitoring, smart cities, transportation logistics, and medical diagnostics [1-11]. These networks rely on a large number of sensor nodes that collect, process, and transmit data while operating under significant resource constraints, such as limited battery power, reduced memory capacity, and potentially intermittent connectivity. In many scenarios, sensors may also be deployed in environments where they can change their location or lose functionality because of mechanical failures or external factors, underscoring the need for robust and adaptive design strategies.

Among the challenges that arise when deploying WSNs, routing remains a key factor influencing overall efficiency and reliability. The routing process involves selecting an optimal path that meets specific performance requirements while minimizing resource consumption. Decisions about routing depend on metrics that characterize the quality of possible routes by considering parameters such as distance, energy consumption, or link quality indicators. These metrics, in turn, guide the algorithm in identifying paths that satisfy criteria for latency and energy usage. Moreover, the distributed and potentially dynamic nature of WSNs necessitates algorithms capable of operating with incomplete or time-varying network information, further emphasizing the need for more robust and adaptable routing solutions.

## II. RELATED WORK

Determining the shortest route in WSNs depends on the distance between two nodes, making the choice of distance metrics a critical factor [12-14]. The Euclidean distance is the most commonly used metric, but other metrics such as Manhattan, Chebyshev, Minkowski, and Hamming distances are also employed, each with its unique characteristics. Therefore, the choice of distance metrics plays a significant role in optimizing data routing.

In our prior research, the focus was on enhancing the reliability of routers by improving their performance and robustness against failures. In contrast, this paper focuses on optimizing routing paths in WSNs using genetic algorithms to enhance network-wide efficiency, minimize energy consumption, and adapt to changes in topology. Solving combinatorial problems in modern networks can be challenging for classical optimization methods due to the high dimensionality of the solution space, dynamic conditions, nonlinearity of objective functions, and multi-criteria requirements [15, 16].

Genetic algorithms (GAs) are powerful tools for solving complex problems, leveraging the principles of natural evolution to find effective solutions amidst a vast number of possibilities [17-23]. These algorithms are also notable for their adaptability to dynamic conditions in the studied environment and their capability for multi-criteria optimization [24-26].

In [27] authors explore the application of GAs to enhance routing efficiency in WSNs. Through simulations, they compare the performance of GAs with traditional algorithms like Dijkstra's and AODV, demonstrating that GAs can effectively adapt to network changes and improve overall performance.

Hamidouche et al., in [28] propose GA-based approaches for clustering and routing aimed at prolonging sensor lifetime and enhancing quality of service. Their extensive simulations indicate that the proposed algorithms outperform existing ones in terms of energy consumption and data delivery to the base station.

Authors in [29] utilize GAs for cluster head election and inter-cluster multi-hopping. Their protocol considers factors like residual energy and distance to the base station, resulting in improved energy efficiency and network lifetime compared to existing algorithms.

In [29] the authors propose a GA-based routing algorithm that selects appropriate cluster heads based on distance to the base station and remaining energy. The algorithm employs GAs to find optimal transmission paths, achieving load balance and reduced energy consumption.

The study [30] addresses the challenges of uniform cluster formation and optimal routing path discovery. The proposed GA-based protocol minimizes network energy consumption and balances load by considering distance metrics in the routing process.

The paper [31] introduces GAEER protocol that selects cluster heads based on residual energy, distance factors, network residual energy, and node density. This approach enhances energy efficiency and extends network lifetime.

In this paper, we focus on commonly used distance metrics, including Euclidean, Manhattan, Chebyshev, and Minkowski, which are widely utilized in WSN routing due to their straightforward implementation and suitability for the studied scenarios. While alternative metrics such as Mahalanobis, cosine, and Jaccard offer significant value in specific applications, they often entail additional computational overhead. These metrics are primarily employed in contexts such as clustering, similarity analysis, and multidimensional data evaluation. Given the practical constraints of WSNs, such as the limited computational resources and the emphasis on energy efficiency, this study omits the Mahalanobis, cosine, and Jaccard metrics to maintain focus on metrics most applicable to the resource-constrained environment of WSN routing.

## II. SYSTEM MODEL

### A. FUNDAMENTALS OF WIRELESS SENSOR NETWORKS

WSNs consist of autonomous sensor nodes deployed over areas of various sizes or in hard-to-reach locations. These nodes operate in a distributed manner without centralized control, ensuring high scalability. This feature allows for the easy addition of new nodes or the removal of existing ones, which is essential for networks requiring adaptation to environmental conditions.

The dynamic topology of WSNs necessitates the use of adaptive routing algorithms capable of rapidly responding to changes in network structure and ensuring reliable data transmission.

The number of nodes in a WSN depends on the specific task, with multiple nodes often sufficient to monitor an entire area. To evaluate this monitoring capability, the concept of coverage degree is used, referring to the number of nodes actively covering a given area. If a portion of the region lacks coverage, it is referred to as a "void." Areas where the sensing ranges of two or more nodes overlap or cover the same physical region constitute sensor overlap zones (Figure 1). Such overlap can offer the following advantages:

- Data collected from overlapping zones allows for additional verification of accuracy and reliability, as multiple nodes contribute to data acquisition.
- If one node fails, another node can cover the same area, helping to mitigate the negative impact on network performance.
- Overlapping zones enable multiple data routing paths, which is particularly critical when dealing with overloaded or malfunctioning nodes.

However, to maximize the network's lifetime, it is necessary to minimize the number of nodes fully covering the monitored area.

Each sensor node can be characterized by two radii [25]: the sensing radius $R_{sens}$ and the communication radius $R_{com}$ (Figure 1). The sensing radius $R_{sens}$ represents the maximum distance at which a node can detect an object or measure specific parameters. The communication radius $R_{com}$ defines the maximum distance at which a node can transmit and receive data from other nodes or a base station.

It is important to note that $R_{com}$ depends on several factors, including the power of the radio transmitter, the frequency range, the presence of interference, and the communication protocols used. In most cases, $R_{com} > R_{sens}$ .

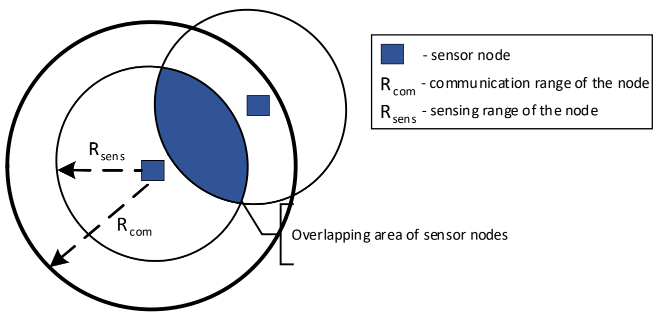



Figure 1. Radius of the node range in WSN

Sensor nodes (SNs) may have varying radii of operation due to a range of technical, operational, and economic factors. The technical specifications of SNs, such as transmitter power, receiver sensitivity, and the type of antennas used, directly influence their operational range.

For instance, nodes with higher transmitter power can cover greater distances, as stronger signals can overcome more obstacles and environmental losses. Similarly, nodes with high receiver sensitivity can detect weaker signals from farther away, increasing their effective range.

Operational factors also play a significant role. Different materials can absorb or reflect radio signals, reducing the nodes' operational range. For example, in urban areas with high building density, the operational range may be limited due to numerous obstacles. Dynamic environmental changes, such as the movement of people, vehicles, or variations in weather conditions, can also affect the propagation of radio signals and, consequently, the nodes' effective range.

Functional requirements within a single WSN can lead to the use of nodes with different operational ranges. For example, some nodes may serve as central nodes or gateways, requiring a larger operational range to communicate with other nodes that have shorter ranges.

### B. DESCRIPTION OF THE GENETIC ALGORITHMS

Genetic algorithms (GAs) are widely studied and applied in various fields due to their ability to efficiently solve complex optimization problems. In the context of WSNs, where traditional optimization methods face several constraints, the use of GAs is particularly relevant.

In WSNs, network information is often incomplete or inaccurate due to limited sensor capabilities, dynamic topology, and environmental factors. GAs can effectively operate under conditions of incomplete information due to their evolutionary nature, which enables them to adapt to new data during the solution search process. These algorithms utilize a population-based approach to generate multiple potential solutions, maintaining high efficiency even with partial knowledge about the network's state.

In GAs, each route is represented as a chromosome, where the genes correspond to the sequence of nodes used for data transmission. By employing selection, crossover, and mutation operators, GAs generate new routes and evaluate their performance using a fitness function that considers one or more required parameters.

The functioning of GAs can be described through four main stages. The process begins with the initialization of a population, representing a set of individuals as possible solutions to the problem. This initial population ensures diversity, allowing the exploration of a broad range of potential solutions and setting the foundation for the evolutionary process, where genetic operators will be applied to these individuals.

The selection phase involves choosing individuals from the current population to form the next generation. Each individual is evaluated and assigned a fitness score reflecting its quality. Once all individuals are assessed, a selection operator identifies the best candidates, maintaining diversity within the population to prevent premature convergence to local optima and increasing the likelihood of finding the globally optimal solution.

The crossover phase simulates the natural process of genetic recombination, promoting evolution by combining traits from high-quality parent solutions. This stage creates new individuals by mixing attributes of the parents, which helps avoid stagnation in local optima by broadening the exploration of the solution space.

The mutation phase introduces random changes to the genetic traits of potential solutions, fostering diversity in the population. This diversity is critical for enabling an effective search for the optimal solution and ensuring the algorithm does not become trapped in suboptimal regions of the solution space.

### C. DISTANCE METRICS

Distance metrics are fundamental components of data routing algorithms in WSNs, as they determine the efficiency of data transmission and the utilization of relevant resources.

A metric is a numerical function that defines the distance (or length of movement) between each pair of considered points. It adheres to the following axioms:

1. Two points with zero distance between them are identical.

2. The distance between two points remains the same regardless of the direction.

3. The distance between two points is always positive.

In the context of routing, metrics are used to determine the optimal route for data transmission. This study focuses on identifying the shortest data route, analyzing the functional characteristics of the primary distance metrics [39].

The Euclidean distance $d_E$ represents the straight-line distance between two points in Euclidean space. In two-dimensional space, the distance between two points with coordinates $(x_1, y_1)$, and $(x_2, y_2)$ can be calculated as:

$$d_E = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}. \quad (1)$$

In higher-dimensional space, the Euclidean distance is defined as:

$$d_E = \sqrt{\sum_{n}^{i=1} (x_i - y_i)^2}, \quad (2)$$

where $n$ represents the dimensionality of the space.

In network topology, nodes can be represented as points in geometric space. The Euclidean distance between these points can serve as a metric for selecting specific routes. In WSNs, minimizing $d_E$ reduces energy consumption, as shorter distances generally require less energy for data transmission. However, $d_E$ does not account for physical obstacles or other network constraints (e.g., technical or resource limitations) that may influence the actual route length. Data normalization is also required before applying this metric. Thus, Euclidean distance is a simple and effective tool for designing communication networks and evaluating routes in WSNs.

The Manhattan distance $d_{MT}$, also known as the taxicab metric, measures the distance between two points in a space where movement is restricted to vertical or horizontal directions. The Manhattan distance calculates the sum of the absolute differences in their Cartesian coordinates. For two points with coordinates $(x_1, y_1)$ and $(x_2, y_2)$, it is defined as:

$$d_{MT} = |x_2 - x_1| + |y_2 - y_1|. \quad (3)$$

In $n$-dimensional space, the Manhattan distance is calculated as:

$$d_{MT} = \sum_{i=1}^{n} |x_i - y_i|. \quad (4)$$

Unlike the Euclidean metric, $d_{MT}$ performs well in higher dimensions but is less intuitive. It is particularly useful for routing in grid-like network topologies where nodes are interconnected with neighboring nodes.

The Chebyshev distance $d_{CH}$, also called the chessboard distance or maximum metric, applies in scenarios where two objects differ by one coordinate dimension, meaning the distance between two points is the greatest difference in their coordinates along any dimension. The term "chessboard distance" originates from the minimal number of moves required for a king to traverse from one square to another in any direction, including diagonals. For two points with coordinates $(x_1, y_1)$, and $(x_2, y_2)$, $d_{CH}$ is defined as:

$$d_{CH} = \max(|x_2 - x_1|, |y_2 - y_1|). \quad (5)$$

Compared to the Manhattan distance, the Chebyshev distance is shorter. This metric is well-suited for networks where nodes can move in all directions, including diagonals.

The Minkowski distance $d_M$ generalizes metrics such as Manhattan, Euclidean, and Chebyshev distances. This metric, also referred to as the $p$-norm vector, includes a parameter $p$ that allows for different distance measurements. For two points $X(x_1, x_2, ..., x_n)$ and $Y(y_1, y_2, ..., y_n)$ is defined as:

$$d_M = \sqrt[p]{\sum_{i=1}^{n} |x_i - y_i|^p}, \quad (6)$$

Special cases include $p = 1$ (Manhattan metric), $p = 2$ (Euclidean metric), and $p = \infty$ (Chebyshev metric). When $p \prec 1$, the result is not a valid metric as it violates the triangle inequality. The Minkowski distance is widely used because of its flexibility in adapting to distance calculations based on various criteria.

## III. WORKFLOW OF THE PROPOSED GENETIC ALGORITHM

To configure the operation of the genetic algorithm (GA), four main parameters were used. Population size $N$ represents the total number of individuals forming the population. Each individual in the population is represented as a chromosome. Thus, this parameter specifies the number of individuals the GA will evaluate simultaneously to solve the problem. The selection of population size depends on the complexity of the problem and the available computational resources. The value is determined experimentally. A larger population size enables a more thorough exploration of the search space, increasing the likelihood of finding the globally optimal solution.

Second parameter is the number of generations $G$, which defines the number of iterations during which the evolution of individuals in the population occurs. The choice of this value depends on the complexity of the problem, the volume of input data, the computational resources, and the desired accuracy of the solution. A greater number of generations allows the algorithm to find more optimal solutions.

Third parameter is the crossover probability $p_{cross}$, which indicates how often genetic material is exchanged between chromosomes in the population. A crossover probability of 0 means that the new generation will be created solely by copying individuals from the current generation, except for those altered by mutation (if mutation is applied).

Finally, the mutation probability $p_{mut}$ specifies the proportion of chromosomes in a generation that should undergo mutation.

To design an effective GA tailored to the specifics of WSNs, appropriate genetic operators were selected, and a fitness function was formulated to evaluate the adaptability of each individual (route). This was based on an analysis of several studies [25, 26, 32, 33]. Adaptive ranges for crossover and mutation probabilities [38] were utilized, such as $p_{cross\_adapt} = [0.5; 0.8]$ and $p_{\mathrm{mut}\_adapt} = [0.05; 0.2]$. The block diagram of the proposed GA for solving the data routing problem is presented in Figure 2.

The fitness of an individual $F(r)_i$ is calculated as

$$F(r)_i = \frac{1}{\sum_{j=1}^{l_i - 1} r_i(j, j+1)}, \quad (7)$$

where $l_i$ – is the length of the individual, corresponding to the number of genes; $r_i$ – represents the individual, which corresponds to the route for data transmission; $(j, j+1)$ is the weight of the edge between two neighboring vertices.

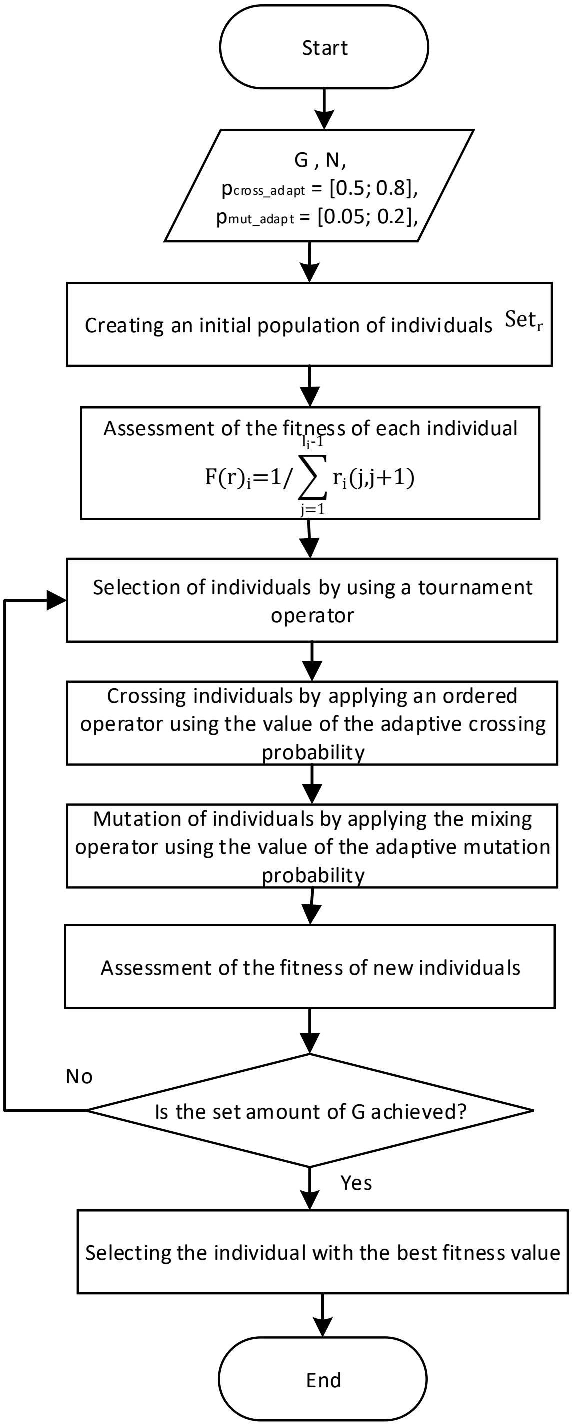



Figure 2. A flow-diagram of the developed genetic algorithm.

According to equation (7), the fitness of an individual is inversely proportional to the weight of the route. It is important to note that the weight can represent various factors, such as distance, the energy reserve of nodes, or the signal-to-noise ratio, depending on the application.

To validate the functionality of the GA presented in Figure 2, modeling was performed using a custom-developed software implemented in Python with the DEAP library. For the simulation, 25 nodes were randomly distributed over a 100×100 m plane (Figure 3). To account for the use of sensor nodes (SNs) with varying operational ranges during the modeling process, it was assumed that the network included SNs with three different ranges, as illustrated in Figure 3.

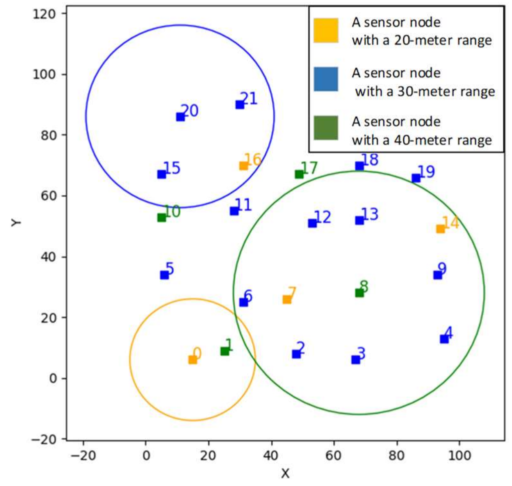



Figure 3. Radiuses of sensor node range

If a node is located farther from another node than the specified radii allow, data transmission becomes impossible. To account for such cases, a penalty of 1000 meters is introduced for the distance. This encourages the genetic algorithm (GA) to prioritize the search for the shortest routes.

## IV. NUMERICAL RESULTS

### *A. RESULTS OF THE DEVELOPED GENETIC ALGORITHM FOR DATA TRANSMISSION ROUTE OPTIMIZATION USING DIFFERENT DISTANCE METRICS*

The simulation of the routing process between nodes 4 and 20 was conducted based on the application of the developed genetic algorithm (GA). Tables 1–4 present the results of route search (distance/time) between the source node (node 4) and the destination node (node 20) for the considered distance metrics. The time complexity was evaluated using the mathematical framework outlined in [26].

**Table 1. Results of Route Search (Distance/Time) for Nodes 4 to 20 Using the GA with the Euclidean Metric**

| Number of Generations | Population Size | | | |
|---|---|---|---|---|
| | 300 | 400 | 500 | 600 |
| 50 | 1000 / 8.3 | 1000 / 10.1 | 1000 / 12.1 | 1000 / 14.4 |
| 100 | 125 / 14.1 | 125 / 18.2 | 125 / 22.3 | 125 / 26.5 |
| 150 | 121 / 20.2 | 121 / 26.3 | 121 / 32.4 | 121 / 38.7 |
| 200 | 121 / 26.2 | 121 / 34.5 | 121 / 42.8 | 121 / 50.7 |
| 250 | 121 / 32.4 | 121 / 42.4 | 121 / 52.6 | 121 / 63.0 |
| 300 | 121 / 38.8 | 121 / 50.8 | 121 / 63.1 | 121 / 75.2 |
| 350 | 121 / 45.9 | 121 / 58.9 | 121 / 73.0 | 121 / 87.8 |
| 400 | 121 / 50.8 | 121 / 66.9 | 121 / 85.2 | 121 / 99.3 |
| 450 | 121 / 57.0 | 121 / 75.1 | 121 / 93.4 | 121 / 111.6 |
| 500 | 121 / 62.8 | 121 / 83.1 | 121 / 103.2 | 121 / 125.3 |
| 550 | 121 / 68.8 | 121 / 91.5 | 121 / 113.9 | 121 / 137.1 |
| 600 | 121 / 74.8 | 121 / 99.4 | 121 / 124.2 | 121 / 149.2 |

**Table 2. Results of Route Search (Distance/Time) for Nodes 4 to 20 Using the GA with the Manhattan Metric**

| Number of Generations | Population Size | | | |
|---|---|---|---|---|
| | 300 | 400 | 500 | 600 |
| 50 | 1000 / 8.2 | 1000 / 10.3 | 1000 / 12.4 | 1000 / 14.2 |
| 100 | 1000 / 14.4 | 1000 / 18.2 | 1000 / 22.3 | 1000 / 26.3 |
| 150 | 165 / 20.3 | 165 / 26.2 | 165 / 32.3 | 165 / 38.5 |
| 200 | 165 / 26.6 | 165 / 34.5 | 165 / 42.5 | 165 / 51.3 |
| 250 | 165 / 32.4 | 165 / 42.6 | 165 / 52.6 | 165 / 63.0 |
| 300 | 165 / 38.7 | 165 / 50.9 | 165 / 62.9 | 165 / 75.1 |
| 350 | 165 / 44.8 | 165 / 58.9 | 165 / 73.0 | 165 / 87.3 |
| 400 | 165 / 50.7 | 165 / 67.1 | 165 / 83.1 | 165 / 99.9 |
| 450 | 165 / 57.0 | 165 / 76.0 | 165 / 93.3 | 165 / 111.7 |
| 500 | 165 / 62.9 | 165 / 83.5 | 165 / 103.9 | 165 / 124.1 |
| 550 | 165 / 69.1 | 165 / 91.4 | 165 / 113.7 | 165 / 140.2 |
| 600 | 165 / 75.4 | 165 / 99.4 | 165 / 124.0 | 165 / 150.1 |

**Table 3. Results of Route Search (Distance/Time) for Nodes 4 to 20 Using the GA with the Chebyshev Metric**

| Number of Generations | Population Size | | | |
|---|---|---|---|---|
| | 300 | 400 | 500 | 600 |
| 50 | 1000 / 8.1 | 1000 / 10.1 | 1000 / 12.1 | 1000 / 14.3 |
| 100 | 111 / 14.3 | 111 / 18.3 | 111 / 22.2 | 111 / 26.4 |
| 150 | 107 / 20.6 | 107 / 26.4 | 107 / 32.2 | 107 / 39.1 |
| 200 | 107 / 27.3 | 107 / 34.4 | 107 / 42.5 | 107 / 51.6 |
| 250 | 107 / 32.8 | 107 / 42.7 | 107 / 53.5 | 107 / 63.5 |
| 300 | 107 / 38.4 | 107 / 51.0 | 107 / 63.4 | 107 / 75.3 |
| 350 | 107 / 44.7 | 107 / 59.8 | 107 / 73.7 | 107 / 87.6 |
| 400 | 107 / 51.3 | 107 / 67.2 | 107 / 84.1 | 107 / 99.5 |
| 450 | 107 / 57.5 | 107 / 75.2 | 107 / 94.0 | 107 / 111.8 |
| 500 | 107/ 63.0 | 107 /83.4 | 107/105.4 | 107/ 124.0 |
| 550 | 107/ 69.8 | 107 /91.5 | 107/114.6 | 107/ 136.3 |
| 600 | 107/ 75.7 | 107/ 100.5 | 107/124.7 | 107/ 150.4 |

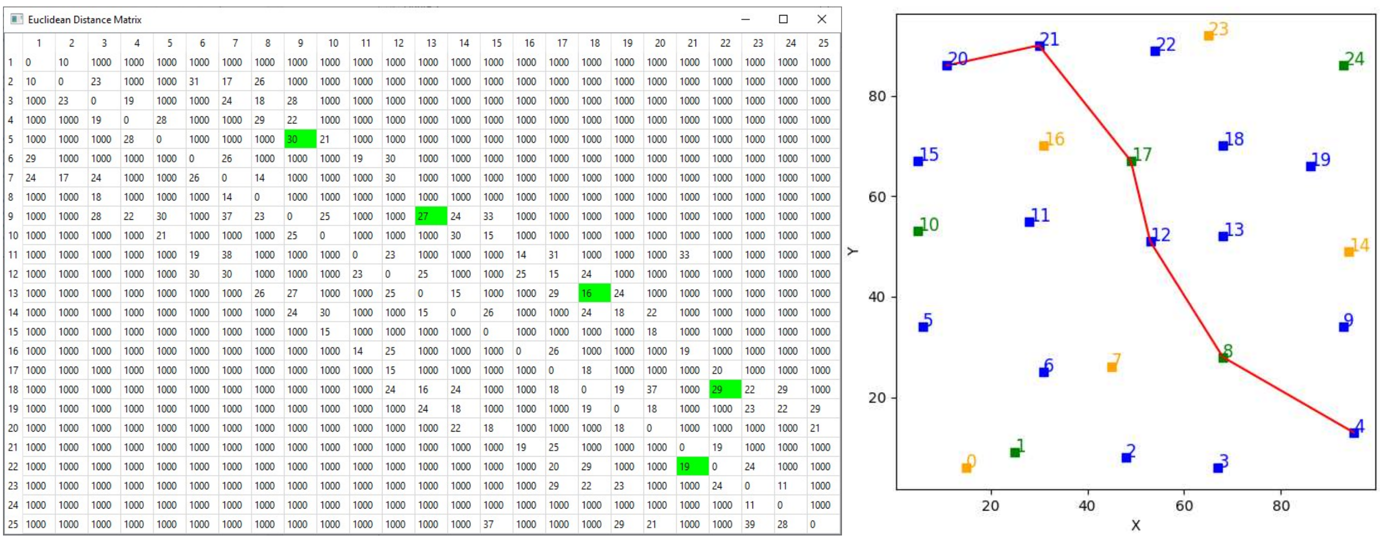
**Table 4. Results of Route Search (Distance/Time) for Nodes 4 to 20 Using the GA with the Minkowski Metric**

| Number of Generations | Population Size | | | |
|---|---|---|---|---|
| | 300 | 400 | 500 | 600 |
| 50 | 1000 / 8.1 | 1000 / 10.5 | 1000 / 12.2 | 1000 / 14.4 |
| 100 | 116 / 14.2 | 116 / 18.3 | 116 / 22.4 | 116 / 26.5 |
| 150 | 113 / 20.6 | 113 / 26.5 | 113 / 32.5 | 113 / 39.2 |
| 200 | 113 / 26.4 | 113 / 35.0 | 113 / 42.5 | 113 / 51.2 |
| 250 | 113 / 32.5 | 113 / 42.8 | 113 / 53.1 | 113 / 63.2 |
| 300 | 113 / 39.0 | 113 / 51.0 | 113 / 63.5 | 113 / 75.9 |
| 350 | 113 / 45.0 | 113 / 59.2 | 113 / 72.9 | 113 / 87.9 |
| 400 | 113 / 50.9 | 113 / 67.4 | 113 / 83.7 | 113 / 99.9 |
| 450 | 113 / 58.1 | 113 / 75.8 | 113 / 93.8 | 113 / 113.1 |
| 500 | 113 / 63.2 | 113 / 84.2 | 113 / 105.6 | 113 / 124.8 |
| 550 | 113 / 69.8 | 113 / 92.3 | 113 / 113.8 | 113 / 137.6 |
| 600 | 113 / 75.6 | 113 / 100.7 | 113 / 124.3 | 113 / 149.9 |

The experimental data presented in Tables 1–4 demonstrate that the optimal parameter values for the genetic algorithm (GA), which achieve the shortest route with minimal computational time, are dependent on the specific distance metric applied. These results underscore the critical need to adapt the algorithm's parameters to the unique characteristics of the chosen metric, ensuring efficient and reliable routing optimization.

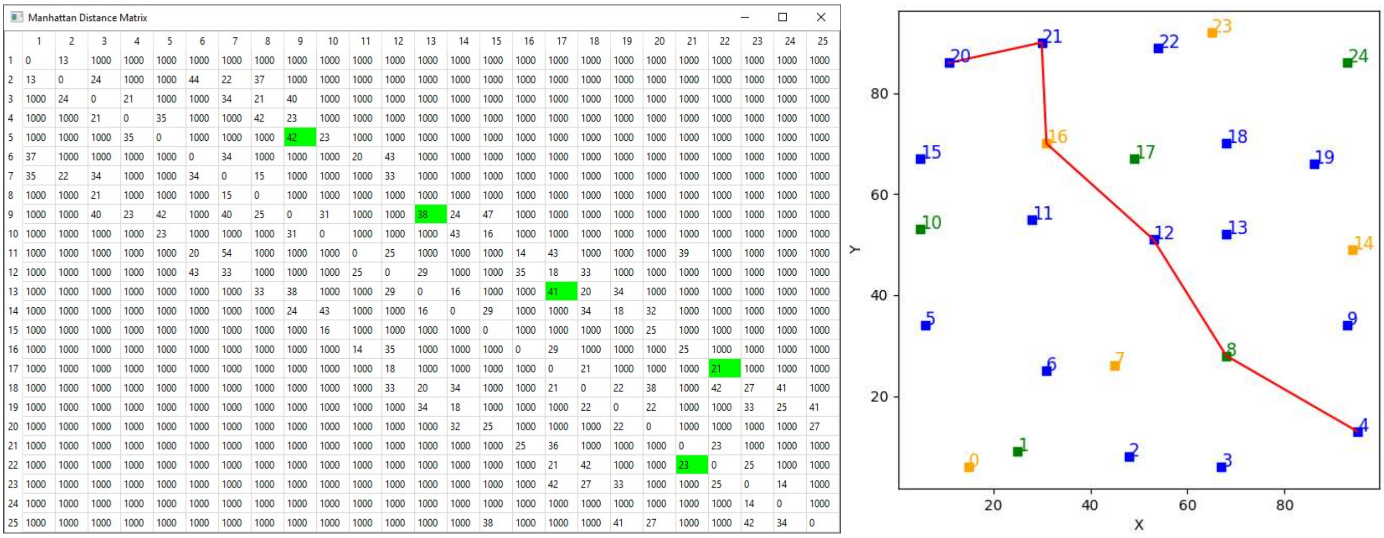
A comprehensive analysis of the routes generated by the GA includes examining the sequence of nodes that form each identified path. This detailed evaluation provides valuable insights into the algorithm's capacity to adapt to varying network topologies and dynamic conditions.

Figures 4–7 illustrate the distance matrices and the corresponding routes generated using the Euclidean, Manhattan, Chebyshev, and Minkowski metrics, highlighting how different metrics influence route formation and the algorithm's decision-making process.




a) b)

Figure 4. Distance Matrix – a) and Generated Route – b) for the Euclidean Metric.



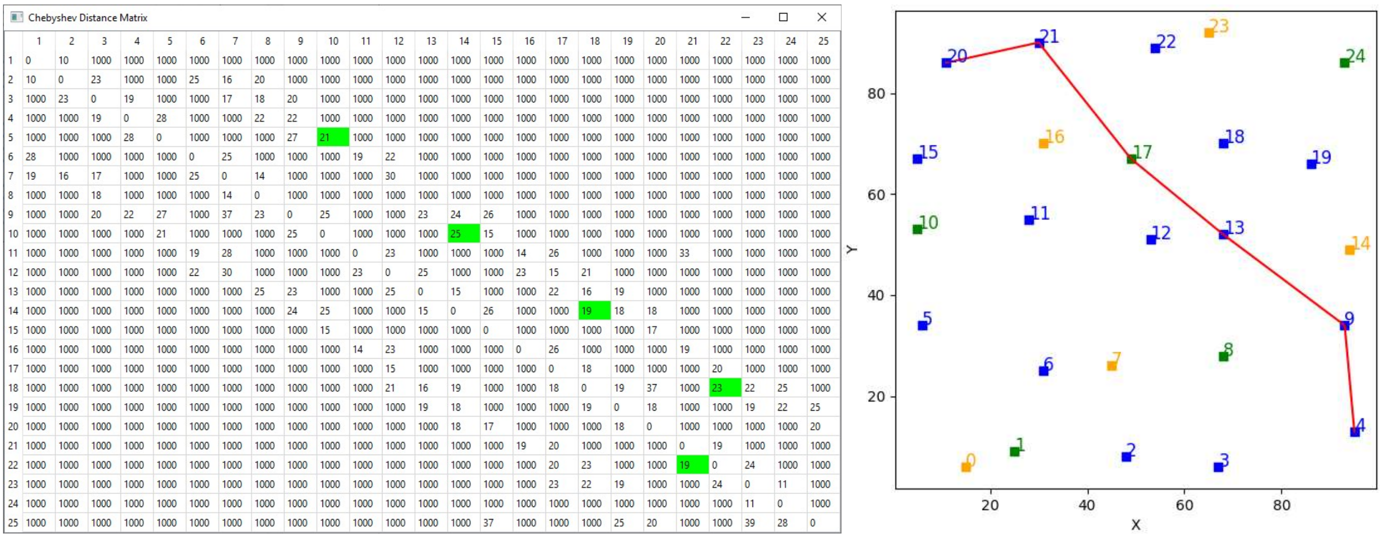
Manhattan Distance Matrix

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 2 | 13 | 0 | 24 | 1000 | 1000 | 44 | 22 | 37 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 3 | 1000 | 24 | 0 | 21 | 1000 | 1000 | 34 | 21 | 40 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 4 | 1000 | 1000 | 21 | 0 | 35 | 1000 | 1000 | 42 | 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 5 | 1000 | 1000 | 1000 | 35 | 0 | 1000 | 1000 | 1000 | 42 | 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 6 | 37 | 1000 | 1000 | 1000 | 1000 | 0 | 34 | 1000 | 1000 | 1000 | 20 | 43 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 7 | 35 | 22 | 34 | 1000 | 1000 | 34 | 0 | 15 | 1000 | 1000 | 1000 | 33 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 8 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 | 15 | 0 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 9 | 1000 | 1000 | 40 | 23 | 42 | 1000 | 40 | 25 | 0 | 31 | 1000 | 1000 | 38 | 24 | 47 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 10 | 1000 | 1000 | 1000 | 1000 | 23 | 1000 | 1000 | 1000 | 31 | 0 | 1000 | 1000 | 1000 | 43 | 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 11 | 1000 | 1000 | 1000 | 1000 | 1000 | 20 | 54 | 1000 | 1000 | 1000 | 0 | 25 | 1000 | 1000 | 1000 | 14 | 43 | 1000 | 1000 | 1000 | 39 | 1000 | 1000 | 1000 | 1000 |
| 12 | 1000 | 1000 | 1000 | 1000 | 1000 | 43 | 33 | 1000 | 1000 | 1000 | 25 | 0 | 29 | 1000 | 1000 | 35 | 18 | 33 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 33 | 38 | 1000 | 1000 | 29 | 0 | 16 | 1000 | 1000 | 41 | 20 | 34 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 14 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 24 | 43 | 1000 | 1000 | 16 | 0 | 29 | 1000 | 1000 | 34 | 18 | 32 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 16 | 1000 | 1000 | 1000 | 1000 | 0 | 1000 | 1000 | 1000 | 1000 | 25 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 14 | 35 | 1000 | 1000 | 1000 | 0 | 29 | 1000 | 1000 | 1000 | 25 | 1000 | 1000 | 1000 | 1000 |
| 17 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 18 | 1000 | 1000 | 1000 | 1000 | 0 | 21 | 1000 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 |
| 18 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 33 | 20 | 34 | 1000 | 1000 | 21 | 0 | 22 | 38 | 1000 | 42 | 27 | 41 | 1000 |
| 19 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 34 | 18 | 1000 | 1000 | 1000 | 22 | 0 | 22 | 1000 | 1000 | 33 | 25 | 41 |
| 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 32 | 25 | 1000 | 1000 | 1000 | 22 | 0 | 1000 | 1000 | 1000 | 1000 | 27 |
| 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 25 | 36 | 1000 | 1000 | 1000 | 0 | 23 | 1000 | 1000 | 1000 |
| 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 21 | 42 | 1000 | 1000 | 23 | 0 | 25 | 1000 | 1000 |
| 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 42 | 27 | 33 | 1000 | 1000 | 25 | 0 | 14 | 1000 |
| 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 14 | 0 | 1000 |
| 25 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 38 | 1000 | 1000 | 1000 | 41 | 27 | 1000 | 1000 | 42 | 34 | 0 |



a) b)

Figure 5. Distance Matrix – a) and Generated Route – b) for the Manhattan Metric.



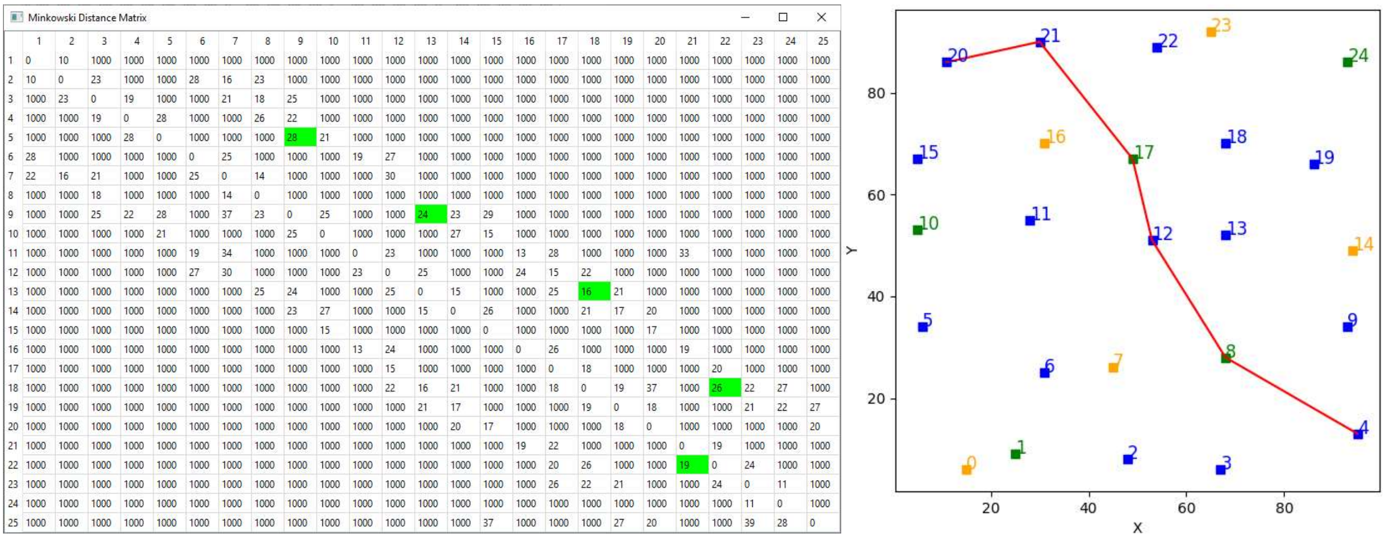
Chebyshev Distance Matrix

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 10 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 2 | 10 | 0 | 23 | 1000 | 1000 | 25 | 16 | 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 3 | 1000 | 23 | 0 | 19 | 1000 | 1000 | 17 | 18 | 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 4 | 1000 | 1000 | 19 | 0 | 28 | 1000 | 1000 | 22 | 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 5 | 1000 | 1000 | 1000 | 28 | 0 | 1000 | 1000 | 1000 | 27 | 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 6 | 28 | 1000 | 1000 | 1000 | 1000 | 0 | 25 | 1000 | 1000 | 1000 | 19 | 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 7 | 19 | 16 | 17 | 1000 | 1000 | 25 | 0 | 14 | 1000 | 1000 | 1000 | 30 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 8 | 1000 | 1000 | 18 | 1000 | 1000 | 1000 | 14 | 0 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 9 | 1000 | 1000 | 20 | 22 | 27 | 1000 | 37 | 23 | 0 | 25 | 1000 | 1000 | 23 | 24 | 26 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 10 | 1000 | 1000 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 | 25 | 0 | 1000 | 1000 | 1000 | 25 | 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 11 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 28 | 1000 | 1000 | 1000 | 0 | 23 | 1000 | 1000 | 1000 | 14 | 26 | 1000 | 1000 | 1000 | 33 | 1000 | 1000 | 1000 | 1000 |
| 12 | 1000 | 1000 | 1000 | 1000 | 1000 | 22 | 30 | 1000 | 1000 | 1000 | 23 | 0 | 25 | 1000 | 1000 | 23 | 15 | 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 25 | 23 | 1000 | 1000 | 25 | 0 | 15 | 1000 | 1000 | 22 | 16 | 19 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 14 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 24 | 25 | 1000 | 1000 | 15 | 0 | 26 | 1000 | 1000 | 19 | 18 | 18 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 15 | 1000 | 1000 | 1000 | 1000 | 0 | 1000 | 1000 | 1000 | 1000 | 17 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 14 | 23 | 1000 | 1000 | 1000 | 0 | 26 | 1000 | 1000 | 1000 | 19 | 1000 | 1000 | 1000 | 1000 |
| 17 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 15 | 1000 | 1000 | 1000 | 1000 | 0 | 18 | 1000 | 1000 | 1000 | 20 | 1000 | 1000 | 1000 |
| 18 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 21 | 16 | 19 | 1000 | 1000 | 18 | 0 | 19 | 37 | 1000 | 23 | 22 | 25 | 1000 |
| 19 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 18 | 1000 | 1000 | 1000 | 19 | 0 | 18 | 1000 | 1000 | 19 | 22 | 25 |
| 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 18 | 17 | 1000 | 1000 | 1000 | 18 | 0 | 1000 | 1000 | 1000 | 1000 | 20 |
| 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 20 | 1000 | 1000 | 1000 | 0 | 19 | 1000 | 1000 | 1000 |
| 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 20 | 23 | 1000 | 1000 | 19 | 0 | 24 | 1000 | 1000 |
| 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 23 | 22 | 19 | 1000 | 1000 | 24 | 0 | 11 | 1000 |
| 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 11 | 0 | 1000 |
| 25 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 37 | 1000 | 1000 | 1000 | 25 | 20 | 1000 | 1000 | 39 | 28 | 0 |



a) b)

Figure 6. Distance Matrix – a) and Generated Route – b) for the Chebyshev Metric.



Minkowski Distance Matrix

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 10 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 2 | 10 | 0 | 23 | 1000 | 1000 | 28 | 16 | 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 3 | 1000 | 23 | 0 | 19 | 1000 | 1000 | 21 | 18 | 25 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 4 | 1000 | 1000 | 19 | 0 | 28 | 1000 | 1000 | 26 | 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 5 | 1000 | 1000 | 1000 | 28 | 0 | 1000 | 1000 | 1000 | 28 | 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 6 | 28 | 1000 | 1000 | 1000 | 1000 | 0 | 25 | 1000 | 1000 | 1000 | 19 | 27 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 7 | 22 | 16 | 21 | 1000 | 1000 | 25 | 0 | 14 | 1000 | 1000 | 1000 | 30 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 8 | 1000 | 1000 | 18 | 1000 | 1000 | 1000 | 14 | 0 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 9 | 1000 | 1000 | 25 | 22 | 28 | 1000 | 37 | 23 | 0 | 25 | 1000 | 1000 | 24 | 23 | 29 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 10 | 1000 | 1000 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 | 25 | 0 | 1000 | 1000 | 1000 | 27 | 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 11 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 34 | 1000 | 1000 | 1000 | 0 | 23 | 1000 | 1000 | 1000 | 13 | 28 | 1000 | 1000 | 1000 | 33 | 1000 | 1000 | 1000 | 1000 |
| 12 | 1000 | 1000 | 1000 | 1000 | 1000 | 27 | 30 | 1000 | 1000 | 1000 | 23 | 0 | 25 | 1000 | 1000 | 24 | 15 | 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 25 | 24 | 1000 | 1000 | 25 | 0 | 15 | 1000 | 1000 | 25 | 16 | 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 14 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 23 | 27 | 1000 | 1000 | 15 | 0 | 26 | 1000 | 1000 | 21 | 17 | 20 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 15 | 1000 | 1000 | 1000 | 1000 | 0 | 1000 | 1000 | 1000 | 1000 | 17 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 13 | 24 | 1000 | 1000 | 1000 | 0 | 26 | 1000 | 1000 | 1000 | 19 | 1000 | 1000 | 1000 | 1000 |
| 17 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 15 | 1000 | 1000 | 1000 | 1000 | 0 | 18 | 1000 | 1000 | 1000 | 20 | 1000 | 1000 | 1000 |
| 18 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 22 | 16 | 21 | 1000 | 1000 | 18 | 0 | 19 | 37 | 1000 | 26 | 22 | 27 | 1000 |
| 19 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 21 | 17 | 1000 | 1000 | 1000 | 19 | 0 | 18 | 1000 | 1000 | 21 | 22 | 27 |
| 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 20 | 17 | 1000 | 1000 | 1000 | 18 | 0 | 1000 | 1000 | 1000 | 1000 | 20 |
| 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 22 | 1000 | 1000 | 1000 | 0 | 19 | 1000 | 1000 | 1000 |
| 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 20 | 26 | 1000 | 1000 | 19 | 0 | 24 | 1000 | 1000 |
| 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 26 | 22 | 21 | 1000 | 1000 | 24 | 0 | 11 | 1000 |
| 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 11 | 0 | 1000 |
| 25 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 37 | 1000 | 1000 | 1000 | 27 | 20 | 1000 | 1000 | 39 | 28 | 0 |



a) b)

Figure 7. Distance Matrix – a) and Generated Route – b) for the Minkowski Metric.

The experimental findings further validate that, for the given scenario, the most effective configuration of the GA involves setting the number of generations to 150 and the population size to 300.

This specific configuration achieves an optimal balance between computational efficiency and route optimization, enabling the algorithm to deliver high-performance results while maintaining manageable computational overhead. These outcomes demonstrate the robustness and adaptability of the proposed approach to addressing the routing challenges inherent in wireless sensor networks.

### *B. RESULTS OF THE GREEDY ALGORITHM FOR DATA TRANSMISSION ROUTE OPTIMIZATION USING DIFFERENT DISTANCE METRICS*

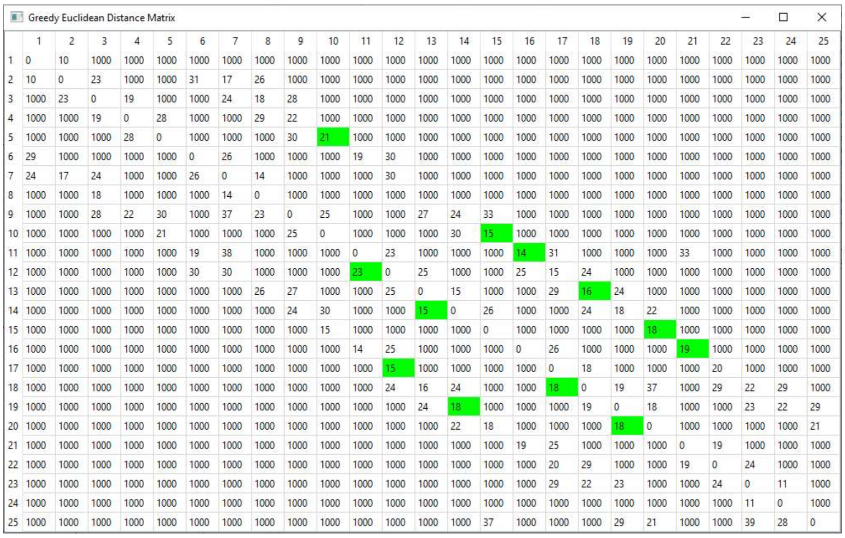
To evaluate the efficiency of the presented genetic algorithm (GA), it was compared with a greedy algorithm, a classical heuristic approach [34-37]. The choice of the greedy algorithm was motivated by its simplicity of implementation and high processing speed. In this algorithm, each node makes decisions about the next step based on the minimum distance to the next available node. This reduces the algorithm's complexity and decreases computational resource usage.

The greedy algorithm operates based on local search, meaning nodes do not possess information about the global structure of the network or all possible routes. Instead, they work with limited information, which reduces the computational burden.

The localized decision-making nature of this algorithm enables quick responses to network changes, such as node failures or additions. There is no need for a complete reconfiguration of the data transmission route. Each node can independently make new decisions based on updated information about its neighbors, positively impacting the overall reliability of the network.

One of the main advantages of the greedy algorithm is its scalability, making it suitable for use in large networks. Consequently, this type of algorithm is rationally applicable for data routing in networks with dynamically changing topology, particularly in WSNs.

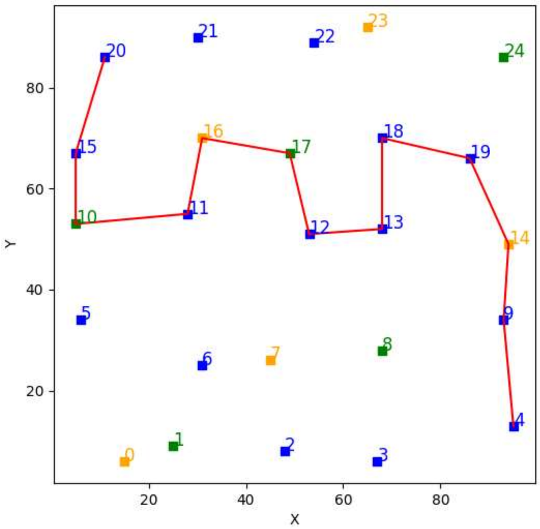
Distance matrices and routes constructed using the greedy algorithm for the considered distance metrics are presented in Figures 8–11.



Greedy Euclidean Distance Matrix

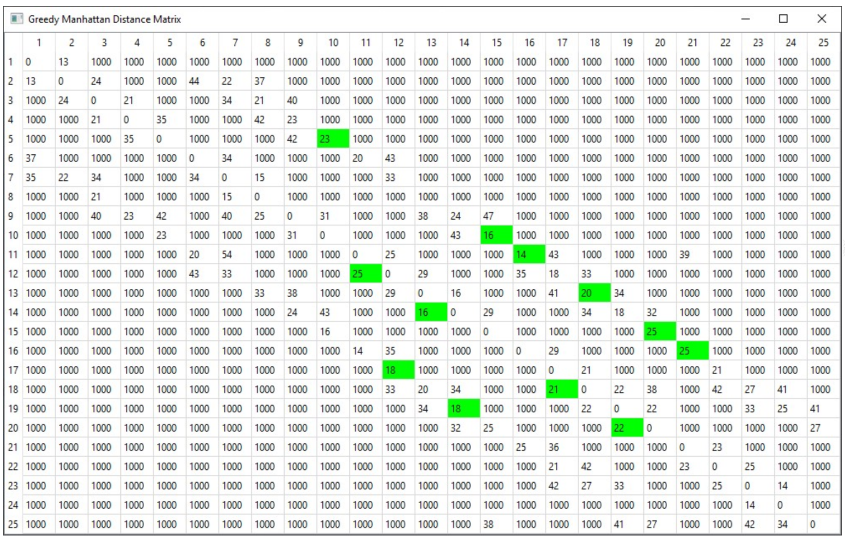
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 10 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 2 | 10 | 0 | 23 | 1000 | 1000 | 31 | 17 | 26 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 3 | 1000 | 23 | 0 | 19 | 1000 | 1000 | 24 | 18 | 28 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 4 | 1000 | 1000 | 19 | 0 | 28 | 1000 | 1000 | 29 | 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 5 | 1000 | 1000 | 1000 | 28 | 0 | 1000 | 1000 | 1000 | 30 | 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 6 | 29 | 1000 | 1000 | 1000 | 1000 | 0 | 26 | 1000 | 1000 | 1000 | 19 | 30 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 7 | 24 | 17 | 24 | 1000 | 1000 | 26 | 0 | 14 | 1000 | 1000 | 1000 | 30 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 8 | 1000 | 1000 | 18 | 1000 | 1000 | 1000 | 14 | 0 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 9 | 1000 | 1000 | 28 | 22 | 30 | 1000 | 37 | 23 | 0 | 25 | 1000 | 1000 | 27 | 24 | 33 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 10 | 1000 | 1000 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 | 25 | 0 | 1000 | 1000 | 1000 | 30 | 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 11 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 38 | 1000 | 1000 | 1000 | 0 | 23 | 1000 | 1000 | 1000 | 14 | 31 | 1000 | 1000 | 1000 | 33 | 1000 | 1000 | 1000 | 1000 |
| 12 | 1000 | 1000 | 1000 | 1000 | 1000 | 30 | 30 | 1000 | 1000 | 1000 | 23 | 0 | 25 | 1000 | 1000 | 25 | 15 | 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 26 | 27 | 1000 | 1000 | 25 | 0 | 15 | 1000 | 1000 | 29 | 16 | 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 14 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 24 | 30 | 1000 | 1000 | 15 | 0 | 26 | 1000 | 1000 | 24 | 18 | 22 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 15 | 1000 | 1000 | 1000 | 1000 | 0 | 1000 | 1000 | 1000 | 1000 | 18 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 14 | 25 | 1000 | 1000 | 1000 | 0 | 26 | 1000 | 1000 | 1000 | 19 | 1000 | 1000 | 1000 | 1000 |
| 17 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 15 | 1000 | 1000 | 1000 | 1000 | 0 | 18 | 1000 | 1000 | 1000 | 20 | 1000 | 1000 | 1000 |
| 18 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 24 | 16 | 24 | 1000 | 1000 | 18 | 0 | 19 | 37 | 1000 | 29 | 22 | 29 | 1000 |
| 19 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 24 | 18 | 1000 | 1000 | 1000 | 19 | 0 | 18 | 1000 | 1000 | 23 | 22 | 29 |
| 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 22 | 18 | 1000 | 1000 | 1000 | 18 | 0 | 1000 | 1000 | 1000 | 1000 | 21 |
| 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 19 | 25 | 1000 | 1000 | 1000 | 0 | 19 | 1000 | 1000 | 1000 |
| 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 20 | 29 | 1000 | 1000 | 19 | 0 | 24 | 1000 | 1000 |
| 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 29 | 22 | 23 | 1000 | 1000 | 24 | 0 | 11 | 1000 |
| 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 11 | 0 | 1000 |
| 25 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 37 | 1000 | 1000 | 1000 | 29 | 21 | 1000 | 1000 | 39 | 28 | 0 |

a)




b)

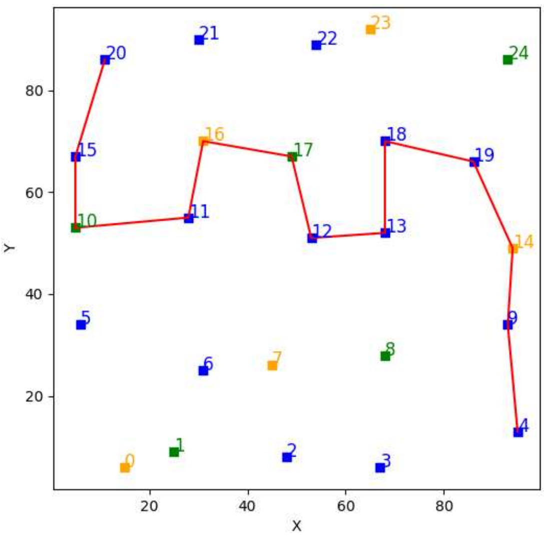
Figure 8. Distance Matrix – a) and Generated Route – b) for the Euclidean Metric.



Greedy Manhattan Distance Matrix

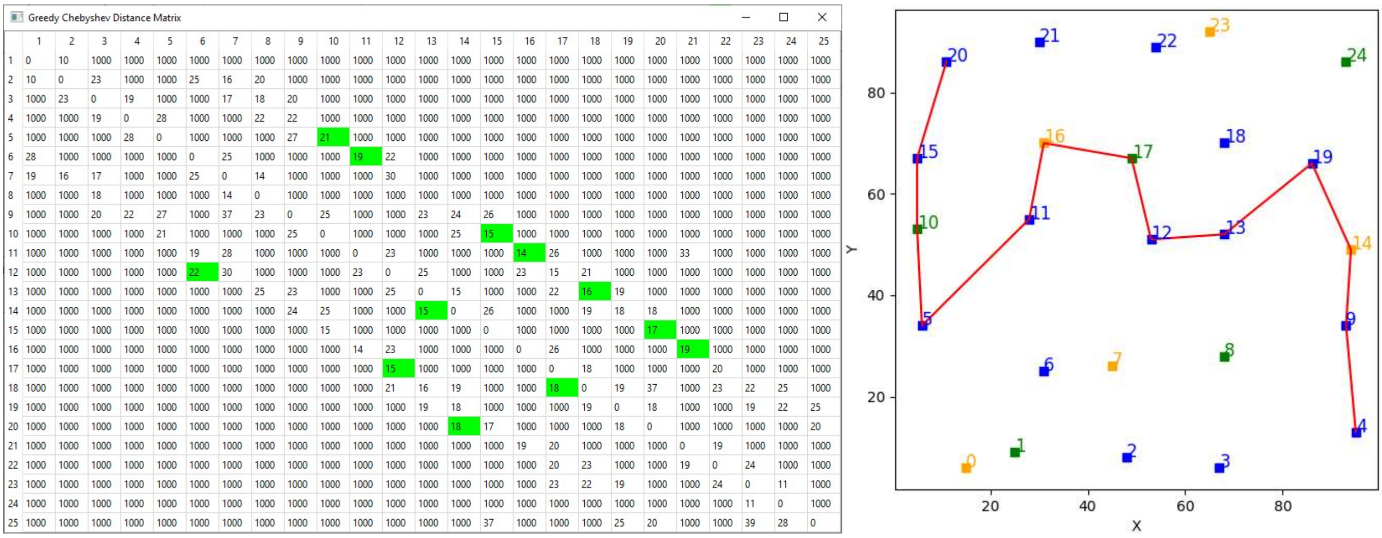
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 2 | 13 | 0 | 24 | 1000 | 1000 | 44 | 22 | 37 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 3 | 1000 | 24 | 0 | 21 | 1000 | 1000 | 34 | 21 | 40 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 4 | 1000 | 1000 | 21 | 0 | 35 | 1000 | 1000 | 42 | 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 5 | 1000 | 1000 | 1000 | 35 | 0 | 1000 | 1000 | 1000 | 42 | 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 6 | 37 | 1000 | 1000 | 1000 | 1000 | 0 | 34 | 1000 | 1000 | 1000 | 20 | 43 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 7 | 35 | 22 | 34 | 1000 | 1000 | 34 | 0 | 15 | 1000 | 1000 | 1000 | 33 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 8 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 | 15 | 0 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 9 | 1000 | 1000 | 40 | 23 | 42 | 1000 | 40 | 25 | 0 | 31 | 1000 | 1000 | 38 | 24 | 47 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 10 | 1000 | 1000 | 1000 | 1000 | 23 | 1000 | 1000 | 1000 | 31 | 0 | 1000 | 1000 | 1000 | 43 | 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 11 | 1000 | 1000 | 1000 | 1000 | 1000 | 20 | 54 | 1000 | 1000 | 1000 | 0 | 25 | 1000 | 1000 | 1000 | 14 | 43 | 1000 | 1000 | 1000 | 39 | 1000 | 1000 | 1000 | 1000 |
| 12 | 1000 | 1000 | 1000 | 1000 | 1000 | 43 | 33 | 1000 | 1000 | 1000 | 25 | 0 | 29 | 1000 | 1000 | 35 | 18 | 33 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 13 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 33 | 38 | 1000 | 1000 | 29 | 0 | 16 | 1000 | 1000 | 41 | 20 | 34 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 14 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 24 | 43 | 1000 | 1000 | 16 | 0 | 29 | 1000 | 1000 | 34 | 18 | 32 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 15 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 16 | 1000 | 1000 | 1000 | 1000 | 0 | 1000 | 1000 | 1000 | 1000 | 25 | 1000 | 1000 | 1000 | 1000 | 1000 |
| 16 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 14 | 35 | 1000 | 1000 | 1000 | 0 | 29 | 1000 | 1000 | 1000 | 25 | 1000 | 1000 | 1000 | 1000 |
| 17 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 18 | 1000 | 1000 | 1000 | 1000 | 0 | 21 | 1000 | 1000 | 1000 | 21 | 1000 | 1000 | 1000 |
| 18 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 33 | 20 | 34 | 1000 | 1000 | 21 | 0 | 22 | 38 | 1000 | 42 | 27 | 41 | 1000 |
| 19 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 34 | 18 | 1000 | 1000 | 1000 | 22 | 0 | 22 | 1000 | 1000 | 33 | 25 | 41 |
| 20 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 32 | 25 | 1000 | 1000 | 1000 | 22 | 0 | 1000 | 1000 | 1000 | 1000 | 27 |
| 21 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 25 | 36 | 1000 | 1000 | 1000 | 0 | 23 | 1000 | 1000 | 1000 |
| 22 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 21 | 42 | 1000 | 1000 | 23 | 0 | 25 | 1000 | 1000 |
| 23 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 42 | 27 | 33 | 1000 | 1000 | 25 | 0 | 14 | 1000 |
| 24 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 14 | 0 | 1000 |
| 25 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 | 38 | 1000 | 1000 | 1000 | 41 | 27 | 1000 | 1000 | 42 | 34 | 0 |

a)



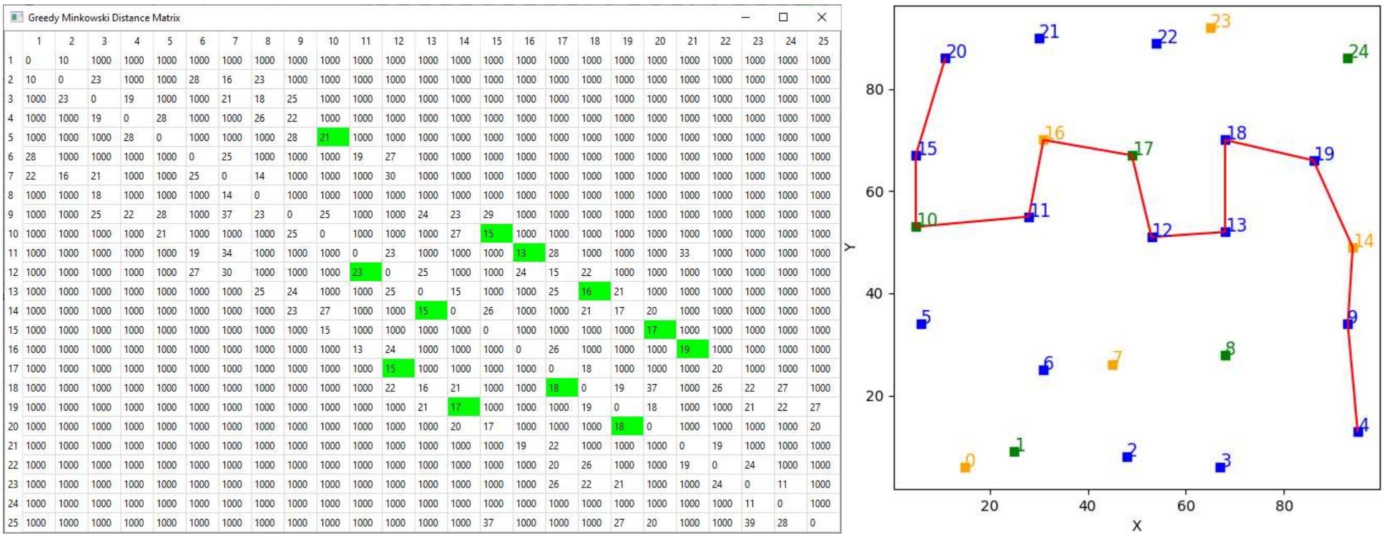

b)

Figure 9. Distance Matrix – a) and Generated Route – b) for the Manhattan Metric.




a) b)

Figure 10. Distance Matrix – a) and Generated Route – b) for the Manhattan Metric.




a) b)

Figure 11. Distance Matrix – a) and Generated Route – b) for the Manhattan Metric.

### *C. COMPARISON OF SIMULATION RESULTS FOR THE GENETIC AND GREEDY ALGORITHMS*

To provide a clearer comparison of the performance of the discussed algorithms, the simulation results are summarized in Table 5.

**Table 5. Comparison of Routes Generated by the Developed Genetic Algorithm and the Classical Greedy Algorithm**

| Algorithm | Metric | Generated Route | Route Length |
|---|---|---|---|
| Genetic | Euclidean | [4, 8, 12, 17, 21, 20] | 121 |
| Greedy | Euclidean | [4, 9, 14, 19, 18, 13, 12, 17, 16, 11, 10, 15, 20] | 210 |
| Genetic | Manhattan | [4, 8, 12, 16, 21, 20] | 165 |
| Greedy | Manhattan | [4, 9, 14, 19, 18, 13, 12, 17, 16, 11, 10, 15, 20] | 243 |
| Genetic | Chebyshev | [4, 9, 13, 17, 21, 20] | 107 |
| Greedy | Chebyshev | [4, 9, 14, 19, 13, 12, 17, 16, 11, 5, 10, 15, 20] | 209 |
| Genetic | Minkowski | [4, 8, 12, 17, 21, 20] | 113 |
| Greedy | Minkowski | [4, 9, 14, 19, 18, 13, 12, 17, 16, 11, 10, 15, 20] | 207 |

Based on the results presented in Table 5, it is evident that the developed GA enables the identification of shorter routes while utilizing significantly fewer nodes compared to the greedy algorithm for the considered distance metrics. Specifically, for the Euclidean metric, the proposed genetic algorithm (GA) produced a route that was 42.38% shorter compared to the route generated by the greedy algorithm. For the Manhattan metric, the proposed GA achieved a route that was 32.1% shorter. Similarly, for the Chebyshev metric, the improvement in route length was 48.8%, and for the Minkowski metric, the reduction was 45.41%. These significant improvements across all metrics highlight the efficiency and effectiveness of the proposed GA in optimizing routing paths in wireless sensor networks.

Thus, the developed algorithm is recommended for enhancing the efficiency of data routing in wireless sensor networks (WSNs) when employing various distance metrics.

In addition to evolutionary algorithms, various other optimization techniques, such as gradient-based methods, least squares approaches, and dynamic programming, are commonly used to address optimization tasks. Gradient-based methods are effective for problems with smooth and differentiable objective functions, enabling rapid convergence to local optima. Least squares techniques are particularly effective in scenarios involving data fitting and regression, where minimizing the sum of squared errors is crucial. Dynamic programming is well-suited for problems with overlapping subproblems and optimal substructure, providing exact solutions in cases where the computational complexity is manageable. While this work focuses on evolutionary algorithms due to their adaptability to the nonlinearity, multi-modality, and high-dimensionality often present in wireless sensor network routing, the inclusion of these alternative methods in future analyses could provide a more comprehensive exploration of optimization strategies for routing and related problems.

## V. CONCLUSIONS

This study examines the operational characteristics of wireless sensor networks (WSNs). It describes the genetic operators and key parameters essential for the functioning of a genetic algorithm. The application of various distance metrics is analyzed, and their mathematical foundations are presented. A block diagram of the proposed genetic algorithm for data routing in WSNs with varying node radii is included.

The effectiveness of the developed algorithm is evaluated in comparison with a greedy algorithm for routing between two nodes in a wireless sensor network, using distance metrics such as Euclidean, Manhattan, Chebyshev, and Minkowski. Experimental results indicate that, for the case considered, the optimal parameters for the genetic algorithm to determine the shortest route with minimal computational time are 150 generations and a population size of 300.

The simulation results clearly demonstrate the superiority of the proposed genetic algorithm (GA) over the greedy algorithm in terms of route length optimization. Specifically, the GA achieved substantial reductions in route length, including a 42.38% decrease for the Euclidean metric, a 32.1% reduction for the Manhattan metric, a 48.8% improvement for the Chebyshev metric, and a 45.41% reduction for the Minkowski metric. These results underscore the efficiency and adaptability of the GA in optimizing routing paths across various distance metrics in wireless sensor networks.

Future research could explore additional distance metrics, hybrid optimization techniques, scalability to larger networks, and the impact of real-world environmental factors to further enhance the efficiency and applicability of the proposed algorithm.

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