Reliable Wireless Sensor Network Planning with Multipath Topology through Relay Placement Optimization

Kasyful Amron [1*], Wuryansari M Kusumawinahyu [2], Syaiful Anam [3], Wayan F Mahmudy [4]
[1, 4] Department of Informatics Engineering, Brawijaya University, Malang, Indonesia
[2, 3] Department of Mathematics, Brawijaya University, Malang, Indonesia
Email: [1] kasyful@ub.ac.id, [2] wmuharini@ub.ac.id, [3] syaiful@ub.ac.id, [4] wayanfm@ub.ac.id
*Corresponding Author

***Abstract*—Recent developments in Wireless Sensor Networks (WSN) focus on scalability and reliability. This research addresses the challenge of improving reliability in WSNs through optimal relay placement and multipath topology design. A heuristic method with a Multi-Objective Optimization (MOO) approach is proposed to solve this problem. The proposed method integrates a modified Genetic Algorithm (GA) with Particle Swarm Optimization (PSO) characteristics. The hybrid approach aims to minimize the number of relays and associated communication costs while maintaining network reliability. The method encodes relay positions and quantities into GA chromosomes that are updated by mutation, crossover, and PSO-inspired particle motion. Simulations are performed in a simplified square area with twenty randomly placed sensors, a hundred and thirty-two arranged relays, and a single sink node. As a result, the simulation generated two multipath topologies that offer unique advantages. The first emphasizes relay efficiency (61 relays, with 2096 costs), while the second ensures lower communication costs (64 relays, 1832 costs). Comparisons with alternative algorithms, including Dijkstra, A-star, GA, and PSO, prove the superiority of the proposed approach. The optimum results obtained with a composition of 95% GA and 5% PSO, outperform alternative algorithms in terms of relay efficiency and communication cost. This research contributes to the field by providing a robust solution for designing reliable multipath WSNs with a minimum number of relays.**

Keywords—Wireless Sensor Network; Relay Placement; Multipath Topology; Minimum Relay Number, Minimum Cost; Multi-Objective Optimization; Genetic Algorithms; Particle Swarm Optimization.

I. INTRODUCTION

A large Wireless Sensor Network (WSN) consists of hundreds to thousands of nodes and has a multi-tiered structure [1], [2]. This structure includes three main types of nodes: sensors, relays, and sinks [3]. Sensors are responsible for detecting, collecting, and sending data to the sink through relays [4, [5]. The sink serves as the destination for all collected data [6], [7]. Planning a multi-tiered wireless sensor network (WSN) with heterogeneous nodes is a significant challenge [8]. A variety of methods and approaches have been explored, as thoroughly reviewed by Wang [9].

In recent years, the focus of WSN development has shifted to scalability and reliability, as detailed in [10-12]. Reliability is associated with the formation of topology, especially multipath topology. In the context of WSN, topology is defined by the connectivity between relays [13-17]. As a result, the placement of relays is a critical factor in WSN topology and reliability [18], [19].

This research focuses on planning the multipath topology of WSN to improve reliability with the minimum number of relays. These goals are achieved through optimal relay placement and communication path adjustments. First, each sensor is placed to connect to different relays, creating at least two different communication paths. This increases the probability of successful data transmission [20], [21]. Second, the length of the communication path is limited, which ensures reasonable transmission delays [22], [23]. Success rates and low transmission delays are important aspects that figure out the reliability of a WSN.

In WSN, relay placement has been considered as an optimization problem several times [24], [25]. Two common optimization methods are often used: deterministic and heuristic [26], [27]. Deterministic methods can provide an exact solution, but they struggle with complex problems [28] and often lead to non-deterministic polynomial time-hard (NP-hard) problems [26]. As an alternative, heuristic methods are considered more suitable for solving relay placement problems [29-31], as shown by the plethora of studies using heuristic methods, as discussed in [32-39].

Nevertheless, heuristic optimization often yields less exact solutions [40] because it cannot guarantee feasibility or optimality. Several studies wrote that optimizing one aspect may lead to undesirable consequences for other aspects. Therefore, some researchers adopt the Multi-Objective Optimization (MOO) approach [41-43]. MOO allows the simultaneous optimization of different objectives [44-46]. This approach opens the possibility of achieving the best solutions by mitigating trade-offs between different relay placement considerations.

In this research, the relay placement problem is formulated as a Multi-Objective Optimization Problem (MOP). This research idea builds on previous studies [47] and [48] with improvements in algorithms and simulations. The proposed MOO method uses a modified Genetic Algorithm (GA). This algorithm is chosen for its success in solving various cases [49-56]. Modification of the algorithm implemented by a fusion of GA and Particle Swarm

Optimization (PSO) algorithm. This fusion is intended to improve the search capabilities [57], [58], thereby potentially improving solution quality and convergence speed.

This research contributes through several innovative aspects. First, the optimization is performed during the planning phase. As a result, implementation phase computations such as quality of service (QoS), routing algorithms, scheduling, fault tolerance, and other features can be performed more efficiently.

Second, the formulation of optimization and constraint functions considers numerous factors that may occur in real-world scenarios. The WSN is designed to cover a large area with a minimum number of nodes. The optimization function aims to minimize the number of relays and the communication cost. Constraints are also applied to the degree of connectivity and the number of hops. These constraint functions are implemented to manage the workload of relays [59] and keep the reliability of the WSN [60]. By considering these aspects, the model improves the practicality and technical accuracy of WSNs, making them more effective for real-world applications.

Third, another contribution lies in the proposed modifications to the optimization algorithm. The population generation is performed using both GA and PSO. This approach is expected to increase the efficiency of finding the best solutions [61], [62], thus contributing significantly to improving most WSN topology designs and increasing reliability.

The structure of this research paper is designed into five detailed sections, including: (I) Introduction, summarizing the background and research problems; (II) Research Method, detailing the proposed problem-solving through various scenarios and test plans; (III) Experimental Setup, covering the search and testing of simulation parameters to achieve optimal results; (IV) Results and Discussion, comprehensively discussing simulation results and their relevance to research problems; and (V) Conclusion, as wrapped up of simulation results, complemented with development recommendations for further research.

II. RESEARCH METHOD

Simulations in this research are conducted within a square region. The side length of this region is adjusted to the communication radius of the nodes. The communication radius for sensors, relays, and sinks is assumed to be uniform and is denoted as rad_c. Sensor deployment is carried out randomly around the target. This strategy ensures complete coverage of the target [63], [64].

Next, virtual cells follow a triangular grid pattern across the simulation area, with cell dimensions tailored to the communication radius. Relays are placed only at the vertices of the triangular grid. This placement method ensures that each relay can set up connections with at least two adjacent relays [47], [48]. For example, the interconnectivity between sensors, relays, and the sink within an area of 5 $\times rad_c$ is shown in Fig. 1. The simulation area shown in Fig. 1 includes 7 sensors, 33 relays, and one sink. In this example, each sensor has connections with the three closest relays, except for the sensor S_4.

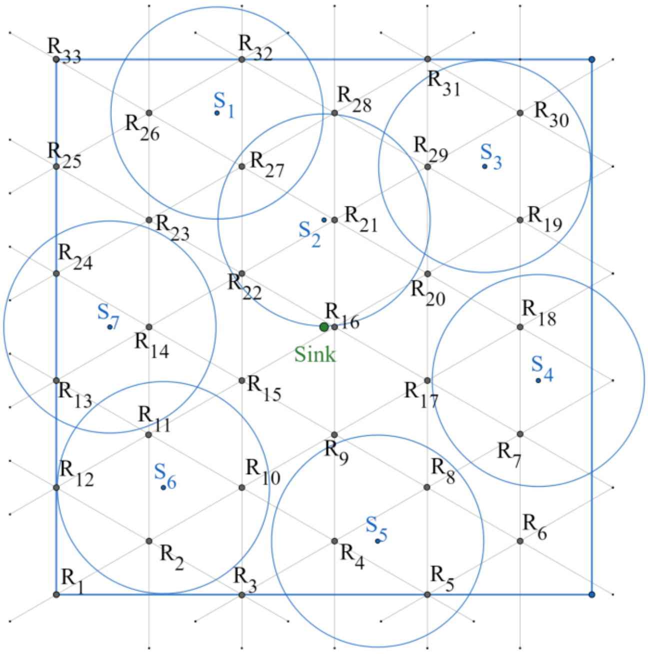


Fig. 1. Example of simulation area

Given the placement pattern previously explained, an estimate of the number of relays needed in each area can be calculated. This process involves mapping all potential locations for these relays, which serve as nodes in the network, according to the triangular pattern formed. To illustrate, in Fig. 1, the total number of relays that can be considered is thirty-three. This number reflects the maximum number of relays that can be placed in the area. It also serves as the size of the constructed GA chromosome. The relationship between the maximum number of relays and the chromosome representation will be discussed in the following sections.

$$MOP = \begin{cases} min\left(\sum N(r_p) + \sum N(r_s)\right) \\ min\left(\sum B(s_p) + \sum B(s_s)\right) \\ k_{max} \geq K(r) \geq k_{min} \\ H_{max} = M \end{cases} \quad (1)$$

In this research, the function of the MOP is described in (1). The number of relay nodes required for the primary path is denoted by $N(r_p)$, while the secondary path is denoted by $N(r_s)$. The communication costs over the primary and secondary paths are expressed as $B(s_p)$ and $B(s_s)$, respectively. The problem is subject to certain constraints. These include the degree of connectivity, denoted by $K(r)$ and the maximum number of hops, denoted by H_{max}.

The constraint function of communication degree, $k_{max} \geq K(r) \geq k_{min}$ referred to as the minimum and maximum number of nodes that can be connected to each relay [65], [66]. This constraint ensures that each relay has an adequate number of connections, thus preventing congestion and excessive energy consumption. Another constraint function is the maximum number of hops, represented as H_{max}. This constraint places a limit on the maximum distance between the sensor and the sink to ensure efficient and reliable data transmission. The determination of this largest hop value considers simulation results and recommendations from previous studies of Wenxing [67] and Sapre [68].

The calculation of communication costs starts with the assignment of cost components for each sensor, relay, and hop [69], [70]. Costs are incurred for each data transmission, including sensor connection $b(s)$, relay usage $b(r)$, and hop usage $b(h)$. Mathematically, the communication cost for a single sensor can be expressed as shown in (2). The terms $\sum_{j=1}^{J} b(r_j)$ and $\sum_{k=1}^{K} b(h_k)$ are the total number of relays and hops used by the sensor to connect to the sink, respectively. As explained in (2), the communication cost is affected by the number of relays and hops required by the sensor. This highlights the importance of efficient relay and hop usage in minimizing the communication cost.

$$B(s_i) = b(s_i) + \sum_{j=1}^{J} b(r_j) + \sum_{k=1}^{K} b(h_k) \tag{2}$$

$$B(wsn) = \sum_{i=1}^{I} B(s_i) \tag{3}$$

$$B(wsn) = \sum_{i=1}^{I} \left(B(s_{ip}) + B(s_{is}) \right) \tag{4}$$

The total communication cost of the WSN is calculated as in (3). This equation is the total communication cost $B(wsn)$ incurred by all sensors $B(s_i)$ cost in the network. To ensure that each sensor has at least two paths, (3) is expanded as shown in (4). In this equation, $B(s_{ip})$ is the communication cost on the primary path, while $B(s_{is})$ is the communication cost on the secondary path. The total costs of all sensors describe the efficiency of the network.

Chromosome development is performed by encoding each relay as a gene with the position corresponding to the order of the relay. The first gene stores information about the first relay, the second gene stores information about the second relay, and so on. If a relay is active at a particular location, the corresponding gene is assigned a value of 1; otherwise, it is assigned a value of 0. Consequently, each chromosome encapsulates information about the number and location of relays used to form the WSN topology. The processes of gene coding, mutation, and crossover of the GA chromosome can be seen in Fig. 2. Using Fig. 1 as an example, each chromosome will have 33 genes, corresponding to the number of potential relay positions in the implementation area.

In a later iteration, new chromosomes are formed using the features of the GA, specifically crossover and mutation [71], [72]. The selection process for each chromosome is controlled by generating random values between 0 and 1 and comparing them to a threshold value. If the generated random value falls below the threshold, the chromosome undergoes mutation in certain genes. In this research, the number of genes subject to mutation is predetermined, while the positions of these genes are randomized. A mutation is implemented by changing the gene values from 0 to 1 or vice versa.

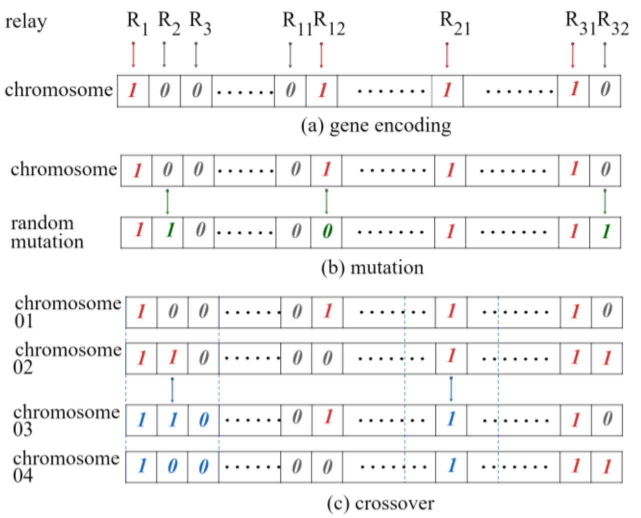


Fig. 2. GA chromosome: (a) gene encoding, (b) mutation, and (c) crossover

If the generated random value exceeds the threshold, the crossover process is started. For this process, two parent chromosomes are randomly selected from the entire population. These selected parent chromosomes are then segmented, and these segments are crossed with segments from other parent chromosomes to form new chromosomes. The size of the gene segments involved in the crossover process is also randomly decided. It is important to note that most new chromosomes are generated by either the mutation or the crossover process. These processes play a critical role in the evolution and optimization of the solution.

In addition to the crossover and mutation processes, chromosome evolution also involves the movement of PSO particles. In this process, each gene in the GA chromosome is treated as a binary PSO particle [73], [74]. The pattern of PSO particles closely follows the structure of the GA chromosome, as shown in Figure 3. Particle positions are updated based on random direction and speed of motion. A particle's position is considered to have changed if its last position exceeds a certain threshold. This change in particle position is the basis for the corresponding change in the gene. The incorporation of PSO particle motion aims to improve the coverage of the search space explored by the GA. This strategy ensures a more comprehensive and effective search for the best solutions.

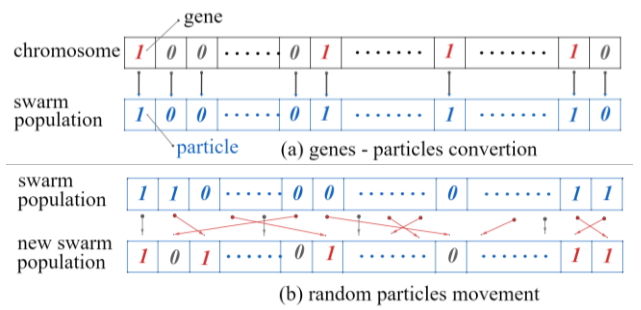


Fig. 3. PSO particle: (a) gene as particle and (b) random particle movement

This modification is expected to improve the optimization results obtained. The integration of GA and PSO considers the distinct characteristics of both algorithms. The exploitative search of GA used in parental selection is combined with the exploratory motion of PSO particles [75]. However, to preserve the fundamental character of GA as the primary algorithm, the implementation of PSO particles is restricted to a small subset of GA chromosomes. This approach ensures that the strengths of both algorithms are leveraged while maintaining the integrity of GA.

Evaluating solutions from each chromosome involves calculating the fitness value of each chromosome. This calculation is based on the number of relays and the communication cost as defined by the MOP in (1). The chromosome that can form a multipath topology with the least number of relays or the lowest communication cost is considered the best. Next, the two chromosomes with the highest fitness values are carried forward to the next iteration. The goal of this step is to ensure that the chromosome population in the next iteration yields a solution that is either better or at least equivalent to the solution from the previous iteration. A flowchart of the optimization method used in this research is shown in Fig. 4.

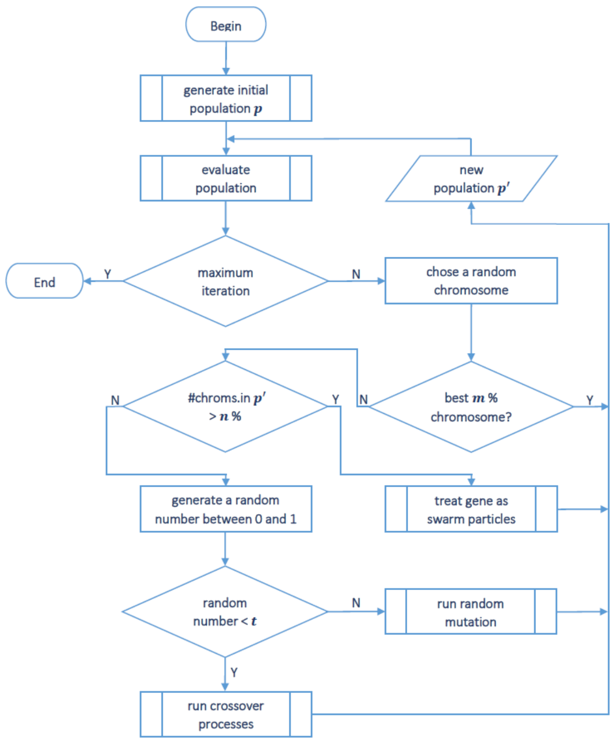


Fig. 4. Flowchart of the proposed method

There are five main steps in this optimization process, namely the initial phase, iteration check, population decomposition and selection, GA and PSO operations, and population update. In the initial phase, the process begins with the generation of an initial population, which represents potential solutions in the search space. Each chromosome is then evaluated using a fitness function that quantifies the quality of the solutions. At the iteration check step, a check is made to see if the maximum number of iterations has been reached. If the number of iterations is less than the maximum, the process continues to the next step.

In the population decomposition phase, the population is divided based on the evaluation results. The best chromosomes are stored for future use. Other chromosomes undergo random crossovers and mutations, creating new genetic variations. Some chromosomes are selected and processed as PSO particles. Their direction and velocity are updated, resulting in new positions in the search space and forming new chromosomes. Finally, the chromosomes are updated based on the new positions of the particles, resulting in a new, improved population. This population then undergoes the same process in the next iteration. This iterative process continues until the maximum number of iterations is reached.

III. EXPERIMENTAL SETTING

The optimization outcomes achieved through the MOO approach heavily rely on the chosen parameters. First simulations were performed within an area of $10rad_c \times 10rad_c$. This simulation area considers the farthest possible distance between sensors and the sink so that WSN reliability is also maintained. Twenty sensors were placed within this area, as shown in Fig. 5. With twenty sensor nodes, it covers more than one-third of the area. This coverage is adequate to monitor scattered target points within the area. The sink node, as the destination for data transmission and storage, was placed in the center of the area. This placement strategy is for easy replication if simulation or implementation with a larger area is desired. For this size of simulation area, a total of 132 relay nodes were required to cover the entire area. This maximum number was then used to construct the corresponding GA chromosome and PSO particle structures.

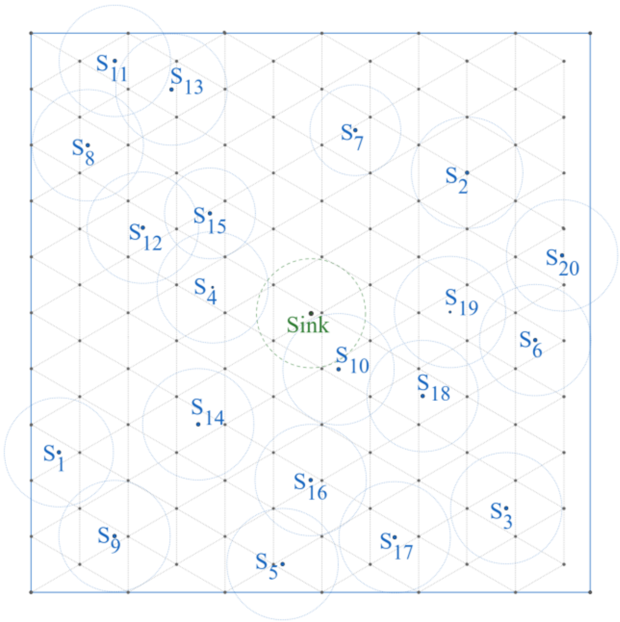


Fig. 5. Simulation area with twenty sensor nodes

In the first simulation, a population of two hundred chromosomes was randomly generated and utilized in a series of iterations. The optimization process was carried out with one thousand iterations. Population ratios, developed as GA chromosomes and PSO particles, were defined in five different combinations: 100:0, 80:20, 60:40, 40:60, and 20:80. A ratio of 100:0 shows that the chromosomes were generated and optimized entirely with GA. This ratio is abbreviated as GP100 for ease of notation. Similarly, GP80 stands for a ratio of 80:20, GP60 for a ratio of 60:40, and so on. The choice of five ratios within a rough range aims to investigate the basic characteristics of the proposed method.

Table I presents a comprehensive overview of the parameter configurations of GP80 utilized in the first simulation. The table outlines the dimensions of the simulation area, sensor locations and quantities, relay placement mappings, and sink location. Additionally, it details communication cost components, penalty values, and constraint functions employed in the simulation. It's important to note that similar metrics were derived by varying percentages of particle randomization. For instance, GP60 denotes a scenario where 60% of the population were chromosomes and the remaining 40% were particles, while other parameters remain the same across configurations.

TABLE I. SIMULATION PARAMETERS

Parameters	**Description/Value**
Simulation area	Square $10rad_c \times 10rad_c$
Position and number of nodes	Sink: 1 node in the center of the simulation area
	Sensors: 20, random position
Algorithm Settings	GA chromosome length: 132 genes (= max. number of relays in the area)
	Population size: 200 chromosomes
	The best 1% of chromosomes are reused
	80% of chromosomes are randomized and reshaped through mutations or crossovers
	The other 20% of chromosomes are treated as particles with random patterns of movement and speed.
	Number of iterations: 1,000
Communication Costs	3-point sensor; 5-point relay; hop 2 points
Limitations (or Penalties)	Degree of connectivity: c_{max}=6, c_{min}=2
	Largest number of hops: 12
	Isolated sensor: 10,000 points
	Single path connection: 5,000 points

Communication costs are associated with diverse types of connections: a three-point sensor connection, a five-point relay connection, and a two-point cost per hop. Penalties are also imposed for certain connectivity issues. The degree of connectivity is bounded by upper and lower limits ($6 \geq K(r) \geq 2$). The maximum number of allowed hops is twelve ($H_{max} = 12$). An isolated sensor incurs a hefty penalty of ten thousand points, while a single path connection results in a penalty of five thousand points. These penalty values are determined based on the communication cost of utilizing all relays in the area to form a multipath topology. This parameters setup is designed to optimize relay deployment and connectivity within the given area, taking into account both communication costs and constraints. If this setup is expressed as a MOP function, it can be represented as follows:

$$MOP = \begin{cases} min \left(\sum N(r_p) + \sum N(r_s)\right) \\ min \left(\sum B(s_p) + \sum B(s_s)\right) \\ 6 \geq K(r) \geq 2 \\ H_{max} = 12 \end{cases} \quad (7)$$

IV. RESULT AND DISCUSSION

The proposed optimization method has demonstrated impressive results in the preliminary simulation. It effectively tackles the predefined MOP model, ensuring that every sensor within the simulation area establishes robust and reliable communication with the sink via two unique paths. Moreover, the method strictly adheres to the existing constraint functions, including connectivity degree and hop count, without any violations. This strict adherence guarantees that the network operates within its specified parameters, thereby boosting its efficiency and reliability.

A detailed examination of the connectivity degree reveals that each relay consistently maintains a specific value. This uniformity indicates a balanced load distribution among the relays, a critical factor in enhancing the network's reliability and performance. The unique attributes of the optimization method, as demonstrated by the preliminary simulation results, are depicted in Fig. 6, Fig. 7, and Fig. 8. These figures provide a visual demonstration of the method's efficacy and underscore its potential.

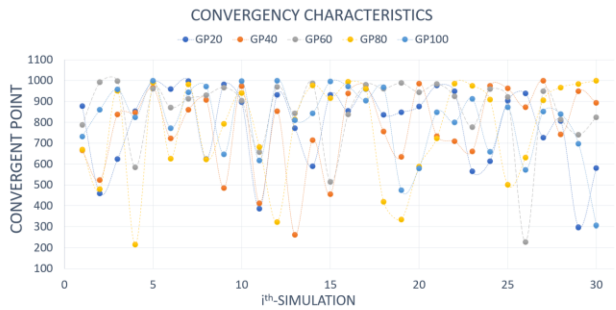


Fig. 6. Simulation result: optimization convergency characteristics

Fig. 6 illustrates the performance of five distinct ratios: GP20, GP40, GP60, GP80, and GP100, evaluated over thirty independent simulations. Upon examination of the provided graph, it is observed that there exists a significant degree of variation in the convergence points across all scenarios throughout the simulations. It is noteworthy that no single scenario consistently yields either the lowest or the highest convergence points. This finding implies that there is no universally optimal ratio of Genetic Algorithm (GA) chromosomes to Particle Swarm Optimization (PSO) particles. However, certain general trends can be discerned from the data. For instance, GP80's significant fluctuations suggest a broad exploration of the solution space, which is beneficial when dealing with complex problems that require extensive exploration to find optimal or near-optimal solutions. Conversely, GP100 begins with a high-performance level and maintains relative stability, indicating strong exploitation capabilities.

This balance between the exploration of GP80 and the exploitation of GP100 can be a strategic choice in many optimization problems. Furthermore, GP100 demonstrates high reliability, making it a rational choice if reliability is a critical factor. Lastly, using both GP80 and GP100 could introduce diversity into the next iteration. The wide exploration of GP80 could bring in novel solutions, while GP100's refinement approach could optimize existing good solutions. This diversity could prevent premature convergence and assist in escaping local optima.

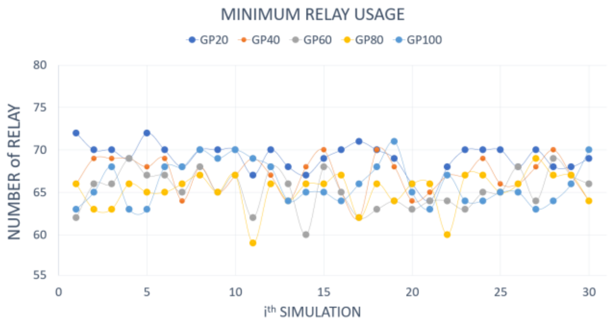


Fig. 7. Simulation result: minimum relay usage

Fig. 7 and Fig. 8 present the simulation results for the number of relays and communication cost, respectively. In addition to the number of relays, communication cost is a crucial parameter, as it significantly affects the overall network topology. Based on Fig. 7, the number of relays varies from a minimum of 59 nodes to a maximum of 72 nodes. The multipath topology with the fewest relays, specifically 59 nodes, is achieved with the GP80 ratio. On average, over thirty tests, GP80 utilizes 65 relay nodes. The GP60 ratio achieves the second-lowest number of relays, 60 nodes, and has an average value of 65 nodes, the same as GP80. For the GP100 ratio, the number of relays ranges from a low of 63 nodes to a high of 71 nodes, with an average value of 66 nodes. Based on these statistics, it can be inferred that three ratios, GP80, GP60, and GP100, outperform others in minimizing relay usage. This performance evaluation gives valuable insights for optimizing the network configuration.

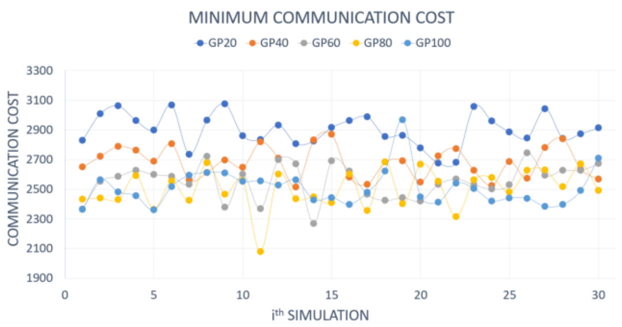


Fig. 8. Simulation result: minimum communication cost

Evaluation of the simulation results based on communication cost yields intriguing insights. As depicted in Fig. 8, the highest communication cost is at 3077 points with the GP20 ratio. In contrast, the lowest cost is achieved with the GP80 ratio, registering at 2078 points. Notably, GP80 records a value approximately 200 points lower than GP60 and 300 points lower than GP100. This value shows the efficiency of the GP80 ratio in minimizing communication costs. When considering the average values, the three most efficient ratios are GP80, GP100, and GP60. These ratios have average values of 2503, 2,510, and 2553 points, respectively. These statistics underscore the effectiveness of these ratios in optimizing communication costs.

The GP20 consistently registers higher communication costs, suggesting potential inefficiency. Both GP40 and GP60 models exhibit considerable variability in communication cost across simulations, indicating inconsistent efficiency. This variability could arise from the inherent randomness in this method or the complexity of the problem space. GP80 generally records lower communication costs than GP20, GP40, and GP60, suggesting potential efficiency. Despite fluctuations, the GP100 model often registers the lowest communication cost, suggesting potential efficiency.

Thus, it can be said that GP80 and GP100 ratios have the best results in terms of communication cost optimization. Overall, based on the results of the preliminary simulation, the best solution for minimizing the number of relays and cost is obtained by modifying the development of GA chromosomes and PSO particles with the GP80 ratio. This parameter is then used in the second simulation with incremental increases of 5% until reaching 100%. Empirical data from the first simulations suggest that ratios with a higher proportion of Genetic Algorithm (GA) chromosomes tend to be more efficient, as evidenced by their lower relay usage. The inclusion of GP100, GP95, GP90, GP85, and GP80 aims to investigate whether a slight reduction in the GA chromosome proportion could lead to a better performance without significantly increasing relay usage.

The results of the second simulation, as depicted in Fig. 9 and Fig. 10, prove enhanced optimization outcomes compared to the earlier simulation. Specifically, the average relay usage in this simulation shows lower values. While the range of relay usage in the earlier simulation was between 65 to 70 nodes, this simulation presents a range between 60 to 65 nodes. The second simulation achieved optimization with the lowest relay usage at 57 nodes and the highest at 67 nodes. These values are smaller compared to the first simulation.

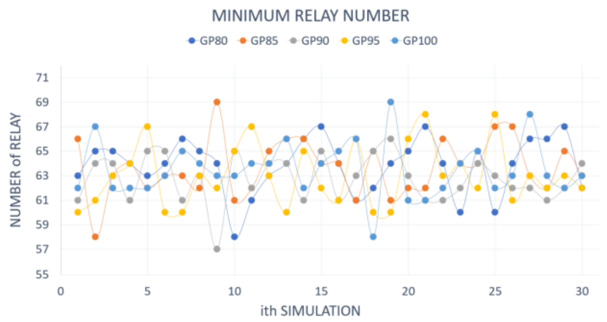


Fig. 9. Minimum relay number of the proposed method

Based on Fig. 9, the best solution is reached with the GP90 ratio, which features the lowest relay usage of 57 nodes. Upon average analysis, the smallest relay usage is reached at two distinct ratios, namely GP90 and GP95, both with 63 relay nodes. The GP80 ratio, which showed the best outcomes in the first simulation, has a range of relay usage from 58 nodes at the lowest to 69 nodes at the highest, with an average relay usage of 64 nodes. The other two ratios, GP85 and GP100, share identical values with GP80. Both have an average value of 64, with the lowest value at 58. These results say that the slightly increasing ratios have effectively enhanced the efficiency of the network configuration. In this second simulation, the GP90 and GP95 ratios yield superior outcomes compared to other ratios, including GP80.

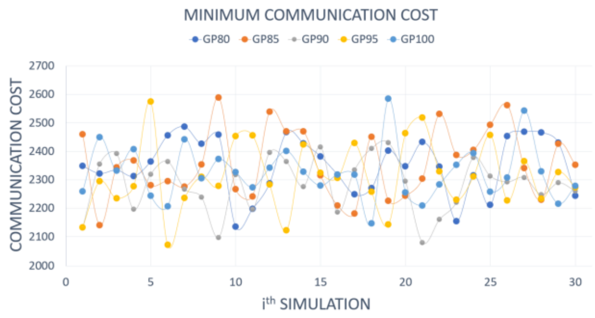


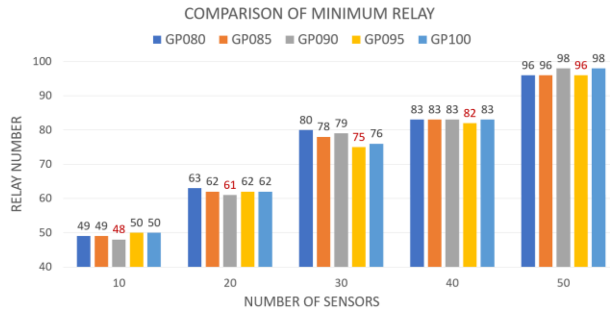
Fig. 10. Minimum communication cost of the proposed method

The second simulation also yielded improved optimization in communication costs, as depicted in Fig. 10. In the first simulation, communication costs fluctuated between 2300 to 2900 points, while the second simulation showed a reduced range of 2100 to 2500 points. The GP95 ratio in the second simulation achieved the minimum communication cost of 2071, which is seven points lower than the first simulation, achieved with the GP80 ratio. Figure 10 reveals that GP90 and GP95 ratios have the lowest average values, 2284 and 2311 respectively, showing their efficiency. Conversely, the GP85 ratio, with the highest average of 2358, appears less efficient. The maximum communication cost in the second simulation was 2589, a significant reduction from the first simulation's maximum of 3077. This data corroborates that an increased iteration limit can yield superior optimization results for communication costs.

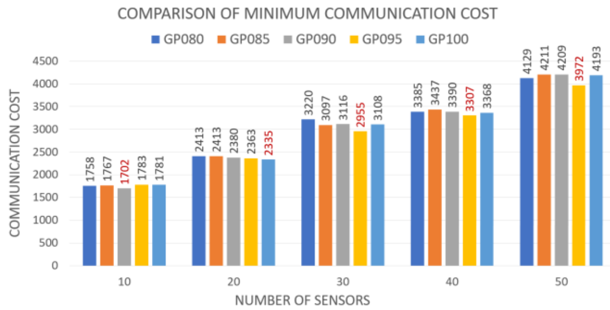
Fig. 11 summarizes the third simulation for relay usage and communication costs with different sensor numbers. Fig. 11(a) presents the relay usage with a varying number of sensors, from 10 to 50 nodes. In the simulation involving ten sensors distributed randomly, the GP90 ratio appeared as the most efficient, generating a network topology with 48 relay nodes. GP80 and GP85 ratios used 49 relays, while GP95 and GP100 employed 50 relays. In the scenario with 20 sensor nodes, the optimization results mirrored the earlier simulation, with the GP90 ratio continuing to deliver the best results, necessitating 61 relays to establish a multipath topology connecting 20 sensors.

Upon examining the average values, GP90 and GP95 stand out as the most efficient ratios, both require an average of 63 relay nodes. However, the simulations involving 30, 40, and 50 sensor nodes yielded different outcomes. In these scenarios, GP095 was the most efficient ratio.

Fig. 11(b) focuses on the optimization of communication costs. The simulation results show that the GP80 yielded the most optimal communication cost in the scenario with 10 sensors, while the GP100 was the most efficient in the 20-sensor scenario. However, in the remaining three scenarios, the GP95 proved to be the best. In the 30-sensor scenario, the GP95 achieved a minimum communication cost of 2955, which is 142 points lower than the next best ratio, GP85, which had a cost of 3097. In the 40-sensor scenario, the GP95 resulted in a communication cost of 3307, outperforming the GP100, which had a minimum communication cost of 3368. In the 50-sensor scenario, the two most efficient ratios were GP95 and GP80, with minimum communication costs of 3972 and 4129, respectively.



(a) minimum relay number



(b) minimum communication cost

Fig. 11. Optimization results for different numbers of sensors

In a more general overview, this method is compared with several other commonly used planning methods in the topology planning process. This comparison includes other algorithms applied to WSNs, such as Dijkstra [76-78], and A-star [79], [80]. Fig. 12 depicts the comparison of relay usage in a scenario with 20 sensor nodes. Both Dijkstra and A-star algorithms use a minimum of 83 relays, with Dijkstra using up to 104 nodes and A-star using up to 117 nodes. In contrast, PSO and GA generate multipath topologies with lower minimum relay counts of 70 and 62 nodes, respectively. On average, PSO needs 74 relay nodes, while GA requires 66 nodes. The average and minimum values both outperform those of Dijkstra or A Star.

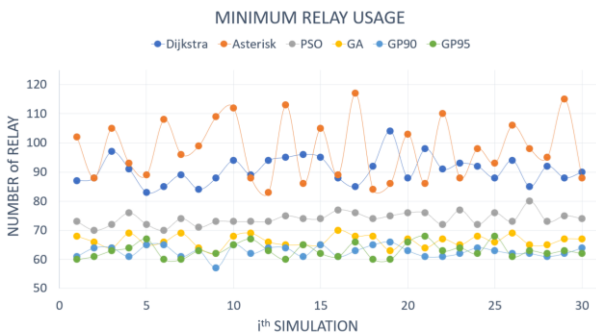


Fig. 12. Comparison of the proposed method and alternative methods

Furthermore, the developed method surpasses PSO or GA. The GP90 has a minimum value of 57 relays and a maximum of 66 relays, with an average of 63 nodes. The GP95 is slightly higher, with a minimum of 60 nodes and a maximum of 68 nodes, but it matches the GP90 with an average of 63 relays. These findings suggest that the GP90 and GP95 ratios have superior optimization results in terms of relay usage.

Lastly, the main output of the proposed method is shown in Fig. 13 and Fig. 14. It serves as an example of the successful formation of multipath WSN topologies. Those figures show how 20 sensor nodes that are randomly placed connect to the sink via two distinct paths. Each of these topologies presents unique advantages. The first topology, depicted in Fig. 13, is advantageous due to its fewer relay usage. On the other hand, the second topology, shown in Fig. 14, stands out for its lower communication costs. These examples underscore the effectiveness of the simulation method in optimizing both relay usage and communication costs, depending on the specific requirements of the network topology.

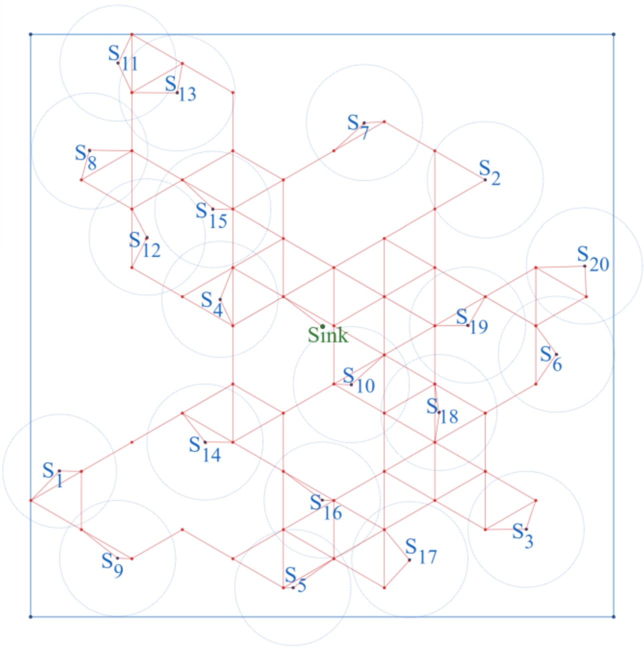


Fig. 13. Multipath topology with minimum relay number

The first topology in Fig. 13 comprises 61 relay nodes with a communication cost of 2096. In this topology, the connectivity degrees of relays range from 2 to 5. Among the 61 relays, 21 have a connectivity degree of 2, 17 relays have a degree of 3, and 17 relays have a degree of 4. The highest connectivity degree of 5 is found in 5 other relay nodes. The average connectivity degree of relays in this topology is 3.10. Meanwhile, the second topology consists of 64 relay nodes. This number is higher than in the first topology but has a lower communication cost of 1832. The second topology in Fig. 14 has an average connectivity degree of 3.30, with the highest connectivity degree being 6, which is higher than in the first topology. This connectivity degree is the maximum allowed during the optimization process. Among the 64 relay nodes, 15 have a connectivity degree of 2, 23 nodes have a degree of 3, 1 node has a maximum degree of 6, and the rest have connectivity degrees of 4 or 5.

In terms of hop count, the first topology does not provide a direct communication path. The shortest path allows sensor nodes to connect to the sink via a single relay node. However, this topology also includes the longest path, spanning 12 hops, which is the maximum distance limit. On average, sensor nodes in the first topology are located 6.9 hops away from the sink. In contrast, the second topology exhibits a range of hop counts, from a minimum of two to a maximum of 10. The average distance between the sensors and the sink in this topology is 6.1 hops, which is shorter than the first topology.

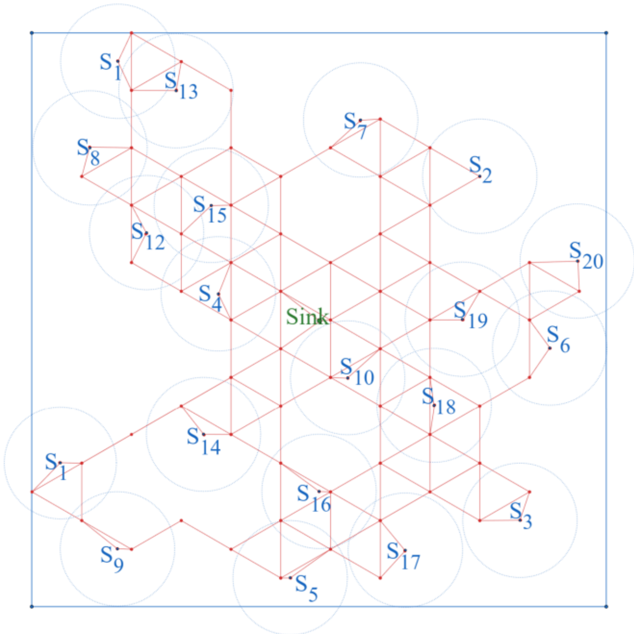


Fig. 14. Multipath topology with minimum communication cost

These observations highlight the importance of considering the range of hop counts, from the shortest to the longest paths, as well as the average distance. It is evident that different topologies offer various advantages, and the selection of topology may depend on whether the priority is to minimize the number of relays, reduce communication costs, or optimize the number of hops.

Assuming the degree of connectivity as a measure of energy consumption, and the number of hops as an indicator for transmission delay, one can deduce the following: The first topology optimizes energy consumption but results in a longer transmission delay. Conversely, the second topology, while being more energy-intensive due to a higher degree of connectivity, ensures a reduced transmission delay due to a lesser number of hops.

In summary, both topologies present distinct advantages and challenges that can be significantly related to the implementation requirement. A topology with fewer relays offers cost efficiency, a crucial factor for large-scale WSNs. However, this efficiency is accompanied by the potential for forming circular paths, thereby increasing the number of hops and data transmission delay. On the other hand, a topology with a larger number of relays, meaning costly, facilitates the formation of paths with fewer hops and reduces data transmission delay. However, this advantage is offset by a higher degree of connectivity, leading to increased energy consumption and potentially, a shorter operational lifespan of the WSNs.

Therefore, the selection of the optimal topology is not a universal decision but rather a strategic choice that depends on the specific requirements. Whether the priority is cost efficiency, transmission speed, energy conservation, or operational longevity, the decision rests with the user or expert, who must balance these factors against the demands of the network.

V. Conclusion

This research presents a multi-objective optimization method for Wireless Sensor Networks using a modified GA that imitates the PSO particle movement. The method aims to optimize the WSN multipath topology by minimizing the relay number and the communication cost. Simulations were run in various scenarios, with parameters including the ratio of GA chromosomes to PSO particles, and sensor number and position. The best results were achieved with a GP90 ratio, where 90% of the 200 chromosomes were developed using GA features, and the remaining 10% were threatened as PSO particles. This method outperformed other algorithms like Dijkstra, A-Star, GA, and PSO in terms of relay usage and communication cost. As the output, the method produced two topology designs based on the multi-objective approach. One design prioritizes cost efficiency with fewer relays, while the other ensures lower communication costs despite having more relays. The choice between these designs depends on whether the user prioritizes cost efficiency or data transmission delay reduction. Further research is needed for a deeper understanding of this method, including but not limited to computational mathematics analysis of fitness functions and constraints, heuristic optimization to determine global or local optimality, and evaluation of optimization results using WSN design software.

Acknowledgment

The authors would like to thank Prof. Dr. Agus Suryanto, M. Sc., Prof. Trisilowati, M. Sc, Ph.D., Prof. Dr. Eng. Agus Naba, M.T., Prof. Dr. Isnani Darti, M.Si., and lecturers of the Faculty of Mathematics and Natural Sciences, Universitas Brawijaya, whose constructive and in-depth views and comments helped improve the presentation of this paper.

References

[1] L. Phan and T. Kim, "Hybrid time synchronization protocol for large-scale wireless sensor networks," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 10423-10433, 2022.

[2] Z. Nurlan, T. Zhukabayeva, M. Othman, A. Adamova, and N. Zhakiyev, "Wireless Sensor Network as a Mesh: Vision and Challenges," *IEEE Access*, vol. 10, pp. 46-67, 2022.

[3] R. I. da Silva, J. D. C. V. Rezende, and M. J. F. Souza, "Collecting large volume data from wireless sensor network by drone," *Ad Hoc Networks*, vol. 138, p. 103017, 2023.

[4] S. Karimi-Bidhendi, J. Guo, and H. Jafarkhani, "Energy-Efficient Node Deployment in Heterogeneous Two-Tier Wireless Sensor Networks with Limited Communication Range," *IEEE Transaction on Wireless Communication*, vol. 20, no. 1, pp. 40–55, 2021.

[5] M. Nikolov and Z. J. Haas, "Relay placement in wireless networks: Minimizing communication cost," *IEEE Transaction on Wireless Communication*, vol. 15, no. 5, pp. 3587–3602, 2016.

[6] S. Veeranami and S. Noor Mohammad, "An Approach to Place Sink Node in Wireless Sensor Network," *Wireless Personal Communication*, vol. 111, pp. 1117-1127, 2020.

[7] E. H. Houssein, M. R. Saad, K. Hussain, W. Zhu, H. Shaban, and M. Hassaballah, "Optimal Sink Node Placement in Large Scale Wireless Sensor Networks Based on Harris' Hawk Optimization Algorithm," *IEEE Access*, vol. 8, pp. 19381-19397, 2020.

[8] A. Shukla and S. Tripathi, "A multi-tier-based clustering framework for scalable and energy-efficient WSN-assisted IoT network," *Wireless Networks*, vol. 26, pp. 3471–3493, 2020.

[9] Z. Wang, H. Xie, D. He, and S. Chan, "Wireless sensor network deployment optimization based on two flower pollination algorithms," *IEEE Access*, vol. 7, pp. 180590–180608, 2019.

[10] C. A. R. Soares, R. de Souza Couto, A. Sztajnberg, and J. L. M. do Amaral, "POSIMNET-R: An immunologic resilient approach to position routers in Industrial Wireless Sensor Networks," *Expert Systems with Applications*, vol. 188, p. 116045, 2022.

[11] D. Zhang, H. Wu, P. Zhao, X. Liu, Y. Cui, L. Chen, and T. Zhang, "New approach of multi-path reliable transmission for marginal wireless sensor network," *Wireless Networks*, vol. 26, no. 2, 2020.

[12] B. A. Attea, M. N. Abbas, M. Al-Ani, and S. Özdemir, "Bio-inspired multi-objective algorithms for connected set K-covers problem in wireless sensor networks," *Soft Computing*, vol. 23, no. 22, pp. 11699–11728, 2019.

[13] A. Dâmaso, N. Rosa, and P. Maciel, "Reliability of Wireless Sensor Networks," *Sensors*, vol. 14, no. 9, pp. 15760–15785, 2014.

[14] A. Mouradian and I. Augé-Blum, "On the Reliability of Wireless Sensor Networks Communications," *Ad-hoc, Mobile, and Wireless Network*, pp. 38-49, 2013.

[15] S. Chakraborty, N. K. Goyal, S. Mahapatra, and S. Soh, "Minimal Path-Based Reliability Model for Wireless Sensor Networks With Multistate Nodes," *IEEE Transactions on Reliability*, vol. 69, no. 1, pp. 382-400, 2020.

[16] H. M. F. AboElfotoh, E. S. Elmallah, and H. S. Hassanein, "On The Reliability of Wireless Sensor Networks," *2006 IEEE International Conference on Communications*, pp. 3455-3460, 2006.

[17] C. Wang, L. Xing, V. M. Vokkarane, and Y. Sun, "Reliability analysis of wireless sensor networks using different network topology characteristics," *International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering*, pp. 12-16, 2012.

[18] S. Chelbi, H. Dhahri, and R. Bouaziz, "Node placement optimization using particle swarm optimization and iterated local search algorithm in wireless sensor networks," *International Journal of Communication Systems*, vol. 34, no. 9, 2021.

[19] S. Sapre and S. Mini, "Optimized Relay Nodes Positioning to Achieve Full Connectivity in Wireless Sensor Networks," *Wireless Personal Communications*, vol. 99, pp. 1521–1540, 2018.

[20] J. Xu, K. Li, and G. Min, "Reliable and Energy-Efficient Multipath Communications in Underwater Sensor Networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 23, no. 7, pp. 1326-1335, 2012.

[21] P. L. Nguyen, T. H. Nguyen, and K. Nguyen, "A Path-Length Efficient, Low-Overhead, Load-Balanced Routing Protocol for Maximum Network Lifetime in Wireless Sensor Networks with Holes," *Sensors*, vol. 20, no. 9, p. 2506, 2020.

[22] K. Sha, J. Gehlot, and R. Greve, "Multipath Routing Techniques in Wireless Sensor Networks: A Survey," *Wireless Personal Communications*, vol. 70, pp. 807–829, 2013.

[23] M. Li, Z. Yin, Y. Ma, C. Wang, A. Chai, and M. Lian, "Design and verification of secure communication scheme for industrial IoT intelligent production line system with multi-path redundancy and collaboration," *Neural Computing and Applications*, vol. 35, pp 13879–13893, 2023.

[24] C. Ma, W. Liang, M. Zheng, and H. Sharif, "A Connectivity-Aware Approximation Algorithm for Relay Node Placement in Wireless Sensor Networks," *IEEE Sensors Journal*, vol. 16, no. 2, pp. 515-528, 2016.

[25] B. Alshaqqawi, S. A. Haque, M. Alreshoodi, and I. Alsukayati, "Enhanced Particle Swarm Optimization for Effective Relay Node Deployment in Wireless Sensor Networks," *International Journal of Computer Networks and Communication – IJCNC*, vol. 13, no.1, 2021.

[26] X. Yang. *Optimization techniques and applications with examples*. John Wiley and Sons, 2018.

[27] G. Gunjan, "A Review on Multi-objective Optimization in Wireless Sensor Networks Using Nature Inspired Meta-heuristic Algorithms," *Neural Processing Letters*, vol. 55, pp. 2587–2611, 2023.

[28] P. Parwekar, S. Rodda, and N. Kalla, “A Study of the Optimization Techniques for Wireless Sensor Networks (WSNs),” in *Advances in Intelligent Systems and Computing*, vol. 672, pp. 909-915, 2018.

[29] H. M. Abdulwahid and A. Mishra, "Deployment Optimization Algorithms in Wireless Sensor Networks for Smart Cities: A Systematic Mapping Study," *Sensors*, vol. 22, no. 14, 2022.

[30] M. Younis and K. Akkaya, "Strategies and techniques for node placement in wireless sensor networks: A survey," *Ad Hoc Networks*, vol. 6, no. 4, pp. 621–655, 2008.

[31] S. Mirjalili and J. S. Dong, "Non-dominated Sorting Genetic Algorithm," in *Multi-Objective Optimization using Artificial Intelligence Techniques*, pp. 37–45, 2020.

[32] M. Sanchez, J. M. Cruz-Duarte, J. C. Ortiz-Bayliss, H. Ceballos, H. Terashima-Marin, and I. Amaya, "A Systematic Review of Hyper-Heuristics on Combinatorial Optimization Problems," *IEEE Access*, vol. 8, pp. 128068–128095, 2020.

[33] N. Samarji and M. Salamah, "A fault tolerance metaheuristic-based scheme for controller placement problem in wireless software-defined networks," *International Journal of Communication Systems*, vol. 34, no. 4, 2021.

[34] S. Singh, A. S. Nandan, A. Malik, N. Kumar, and A. Barnawi, "An Energy-Efficient Modified Metaheuristic Inspired Algorithm for Disaster Management System Using WSNs," *IEEE Sensors Journal*, vol. 21, no. 13, pp. 15398–15408, 2021.

[35] L. Abualigah *et al*., "Meta-heuristic optimization algorithms for solving real-world mechanical engineering design problems: a comprehensive survey, applications, comparative analysis, and results," *Neural Computing and Applications*, vol. 34, no. 6, pp. 4081–4110, 2022.

[36] R. Cerulli, C. D'Ambrosio, A Iossa, and F. Palmieri, "Maximum Network Lifetime Problem with Time Slots and Coverage Constraints: heuristic approaches," *Journal of Supercomputing*, vol. 78, no. 1, 2022.

[37] M. Manju, "A Meta-Heuristic Based Approach with Modified Mutation Operation For Heterogeneous Networks," *Wireless Personal Communications*, vol. 122, no. 2, 2022.

[38] R. K. Yadav and R. P. Mahapatra, "Hybrid metaheuristic algorithm for optimal cluster head selection in Wireless Sensor Network," *Pervasive and Mobile Computing*, vol. 79, 2022.

[39] L. Mostarda, A. Navarra, and R. De Leone, "Optimal vs rotation heuristics in the role of cluster-head for routing in IoT constrained devices," *Internet of Things*, vol. 22, p. 100757, 2023.

[40] A. Srivastava and P. K. Mishra, "A Survey on WSN Issues with its Heuristics and Meta-Heuristics Solutions," *Wireless Personal Communications*, vol. 121, pp. 745–814, 2021.

[41] Z. Lalama, S. Boulfekhar, and F. Semechedine, "Localization Optimization in WSNs Using Meta-Heuristics Optimization Algorithms: A Survey," *Wireless Personal Communications*, vol. 122, pp. 1197–1220, 2022.

[42] M. Iqbal, M. Naeem, A. Anpalagan, A. Ahmed, and M. Azam, "Wireless sensor network optimization: Multi-objective paradigm," *Sensors*, vol. 15, no. 7, pp. 17572–17620, 2015.

[43] Z. Fei, B. Li, S. Yang, C. Xing, H. Chen, and L. Hanzo, "A Survey of Multi-Objective Optimization in Wireless Sensor Networks: Metrics, Algorithms, and Open Problems," *IEEE Communications Surveys and Tutorials*, vol. 19, no. 1, pp. 550–586, 2017.

[44] S. Zhou, Z. Zhan, Z. Chen, S. Kwong, and J. Zhang, "A Multi-Objective Ant Colony System Algorithm for Airline Crew Rostering Problem With Fairness and Satisfaction," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 11, pp. 6784-6798, 2021.

[45] O. Singh, V. Rishiwal, R. Chaudhry, and Y. Mano, "Multi-Objective Optimization in WSN: Opportunities and Challenges," *Wireless Personal Communications*, vol. 121, pp. 127–152, 2021.

[46] M. Sánchez, J. M. Cruz-Duarte, J. c. Ortíz-Bayliss, H. Ceballos, H. Terashima-Marin, and I. Amaya, "A Systematic Review of Hyper-Heuristics on Combinatorial Optimization Problems," *IEEE Access*, vol. 8, pp. 128068-128095, 2020.

[47] K. Amron, W. M. Kusumawinahyu, S. Anam, and W. F. Mahmudy, "Relay nodes placement for optimal coverage, connectivity, and communication of wireless sensor networks: A PSO-based multi-objective optimization research idea," *5th International Conference of Sustainable Informatics and Engineering Technology, SIET 2020*, pp. 177–182, 2020.

[48] K. Amron, W. M. Kusumawinahyu, S. Anam, and W. F. Mahmudy, "Multi-Tier Topology Design of Wireless Sensor Networks using Multi-Objective Particle Swarm Optimization," *7th International Conference of Sustainable Informatics and Engineering Technology, SIET 2022*, pp. 103–110, 2022.

[49] K. Zaimen, M.-E.-A. Brahmia, L. Moalic, A. Abouaissa, and L. Idoumghar, "A Survey of Artificial Intelligence Based WSNs Deployment Techniques and Related Objectives Modeling," *IEEE Access*, vol. 10, pp. 113294–113329, 2022.

[50] C. Ma, W. Liang, M. Zheng, and B. Yang, "Relay Node Placement in Wireless Sensor Networks with Respect to Delay and Reliability Requirements," *IEEE Systems Journal*, vol. 13, no. 3, pp. 2570–2581, 2019.

[51] M. Elhoseny, A. Tharwat, A. Farouk, and A. E. Hassanien, "K-Coverage Model Based on Genetic Algorithm to Extend WSN Lifetime," *IEEE Sensors Letters*, vol. 1, no. 4, pp. 1-4, 2017.

[52] I. Jannoud, Y. Jaradat, M. Z. Masoud, A. Manasrah, and M. Alia, "The Role of Genetic Algorithm Selection Operators in Extending WSN Stability Period: A Comparative Study," *Electronics*, vol. 11, no. 1, p. 28, 2021.

[53] J. Chen, S. H. Sackey, J. H. Anajemba, X. Zhang, and Y. He, "Energy-Efficient Clustering and Localization Technique Using Genetic Algorithm in Wireless Sensor Networks," *Complexity*, vol. 2021, pp. 1-12, 2021.

[54] N. S. Abu, W. M. Bukhari, M. H. Adli, and A. Ma'arif, "Optimization of an Autonomous Mobile Robot Path Planning Based on Improved Genetic Algorithms," *Journal of Robotics and Control (JRC)*, vol. 4, no. 4, pp. 557-571, 2023.

[55] M. Zadehbagheri, A. Ma'arif, R. Ildarabadi, M. Ansarifard, and I. Suwarno, "Design of Multivariate PID Controller for Power Networks Using GEA and PSO," *Journal of Robotics and Control (JRC)*, vol. 4, no. 1, 2023.

[56] B. Alnajjar, A. M. Kadim, R. A. Jaber, N. A. Hasan, E. Q. Ahmed, M. S. M. Altaei, and A. L. Khalaf, "Wireless Sensor Network Optimization Using Genetic Algorithm," *Journal of Robotics and Control (JRC)*, vol. 3, no. 6, 2022.

[57] Z. Al-Ani, A. M. Gujarathi, G. R. Vakili-Nezhaad, and A. H. Al-Muhtaseb, "Hybridization Approach Towards Improving the Performance of Evolutionary Algorithm," *Arabian Journal for Science and Engineering*, vol. 45, pp. 11065–11086, 2020.

[58] A. Maghawry, R. Hodhod, Y. Omar, and M. Kholief, "An Approach to Optimize Multi-objective Problems Using Hybrid Genetic Algorithms Supported by Initial Centroid Selection Optimization Enhanced K-Means Based Selection Operator," in *Artificial Intelligence in Intelligent Systems, Computer Science Online Conference – CSOC*, vol. 2, pp. 64-87, 2021.

[59] M. Peng, W. Liu, T. Wang, and Z. Zeng, "Relay Selection Joint Consecutive Packet Routing Scheme to Improve Performance for Wake-Up Radio-Enabled WSNs," *Wireless Communications and Mobile Computing*, vol. 2020, 2020.

[60] M. Sheikh-Hosseini and S. R. Samareh Hashemi, "Connectivity and coverage constrained wireless sensor nodes deployment using steepest descent and genetic algorithms," *Expert Systems with Applications*, vol. 190, 2022.

[61] D. Zhang and B. Wei, "Comparison between differential evolution and particle swarm optimization algorithms," *2014 IEEE International Conference on Mechatronics and Automation*, pp. 239-244, 2014.

[62] T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle Swarm Optimization: A Comprehensive Survey," *IEEE Access*, vol. 10, pp. 10031-10061, 2022.

[63] H. P. Gupta, P. K. Tyagi, and M. P. Singh, "Regular Node Deployment for k-Coverage in m -Connected Wireless Networks," *IEEE Sensors Journal*, vol. 15, no. 12, pp. 7126–7134, 2015.

[64] J. Amutha, S. Sharma, and J. Nagar, "WSN Strategies Based on Sensors, Deployment, Sensing Models, Coverage and Energy Efficiency: Review, Approaches, and Open Issues," *Wireless Personal Communications*, vol. 111, pp. 1089–1115, 2020.

[65] M. A. Benatia, M. Sahnoun, D. Baudry, A. Louis, A. El-Hami, and B. Mazari, "Multi-Objective WSN Deployment Using Genetic

Algorithms Under Cost, Coverage, and Connectivity Constraints," *Wireless Personal Communications*, vol. 94, pp. 2739–2768, 2017.

[66] A. Zrelli and T. Ezzedine, "A New Approach of WSN Deployment, K-Coverage, and Connectivity in Border Area," *Wireless Personal Communications*, vol. 121, pp. 3365–3381, 2021.

[67] L. Wenxing, W. Muqing, Z. Min, L. Peizhe, and L. Tianze, "Hop count limitation analysis in wireless multi-hop networks," *International Journal of Distributed Sensor Networks*, vol. 13, no. 1, p. 2017, 2017.

[68] S. Sapre and S. Mini, "Moth flame optimization algorithm based on decomposition for placement of relay nodes in WSNs," *Wireless Networks*, vol. 26, pp. 1473-1492, 2020.

[69] T. Wang, Y. Li, G. Wang, J. Cao, M. Z. A. Bhuiyan, and W. Jia, "Sustainable and Efficient Data Collection from WSNs to Cloud," *IEEE Transactions on Sustainable Computing*, vol. 4, no. 2, pp. 252-262, 2019.

[70] A. Seyyedabbasi, F. Kiani, T. Allahviranloo, U. Fernandez-Gamiz, and S. Noeiaghdam, "Optimal data transmission and pathfinding for WSN and decentralized IoT systems using I-GWO and Ex-GWO algorithms," *Alexandria Engineering Journal*, vol. 63, pp. 339-357, 2023.

[71] A. Hassanat, K. Almohammadi, E. Alkafaween, E. Abunawas, A. Hammouri, and V. B. S. Prasath, "Choosing Mutation and Crossover Ratios for Genetic Algorithms—A Review with a New Dynamic Approach," *Information*, vol. 10, no. 12, p. 390, 2019.

[72] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimedia Tools and Applications*, vol. 80, pp. 8091–8126, 2021.

[73] L. Zhai, Z. Yang, and W. Ji, "Understanding Crowd Intelligence in Large-scale Systems: A Hierarchical Binary Particle Swarm Optimization Approach," *Intl. Conference on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*, pp. 728-735, 2020.

[74] B. H. Nguyen, B. Xue, P. Andreae, and M. Zhang, "A New Binary Particle Swarm Optimization Approach: Momentum and Dynamic Balance between Exploration and Exploitation," *IEEE Transactions on Cybernetics*, vol. 51, no. 2, pp. 589–603, 2021.

[75] B. Abhishek, S. Ranjit, T. Shankar, G. Eappen, P. Sivasankar, and A. Rajesh, "Hybrid PSO-HSA and PSO-GA algorithm for 3D path planning in autonomous UAVs," *SN Applied Science*, vol. 2, no. 10, 2020.

[76] M. Abderrahim, H. Hakim, H. Boujemaa, and F. Touati, "Energy-Efficient Transmission Technique based on Dijkstra Algorithm for decreasing energy consumption in WSNs," *19th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering, STA 2019*, pp. 599–604, 2019.

[77] I. Diakhate, B. Niang, A. D. Kora, and R. M. Faye, "Optimizing The Energy Consumption of WSN by Using Energy Efficient Routing Protocol Using Dijkstra Algorithm," *Proceedings - 2nd International Conference on Electronic and Electrical Engineering and Intelligent System, ICE3IS 2022*, pp. 147–152, 2022.

[78] M. Razzaq, G. R. Kwon, and S. Shin, "Energy efficient Dijkstra-based weighted sum minimization routing protocol for WSN," *3rd International Conference on Fog and Mobile Edge Computing, FMEC 2018*, pp. 246–251, 2018.

[79] I. S. Alshawi, L. Yan, W. Pan, and B. Luo, "Lifetime enhancement in wireless sensor networks using fuzzy approach and a-star algorithm," *IEEE Sensors Journal*, vol. 12 no. 10, pp. 3010–3018, 2012.

[80] R. Septiana, I. Soesanti, and N. A. Setiawan, "Evaluation function effectiveness in Wireless Sensor Network routing using A-star algorithm," *Proceedings of 4th International Conference on Cyber and IT Service Management*, pp. 1-5, 2016.