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OPTIMIZATION OF MOBILE FLOW ROUTING IN A WIRELESS SENSOR NETWORK USING HEURISTIC ALGORITHMS

The subject of the study is a wireless sensor network (WSN) with a mobile sink. **The purpose of the work** is to improve the performance of the WSN, increase its lifetime and functionality by reducing the data transmission delay time in the process of polling routers by optimizing the mobile sink route using the most efficient algorithm. To achieve this goal, the following **tasks** must be performed: optimize the route of the WSN mobile stock by solving the traveling salesman problem using the branch and bound method and comparing the conditional average route length of a set of solutions without optimization and with optimization using the Robbins–Monroe procedure; conduct a comparative analysis of the exact solution of the traveling salesman problem obtained by the branch and bound method and the approximate solution obtained by heuristic methods; formulate practical recommendations for the selection of algorithms for optimizing the mobile flow route depending on the size of the sensor network. The following **methods** were used: simulation modeling, optimization methods, mathematical data processing. **Results achieved.** The solution of the mobile flow route optimization problem in BSM using heuristic algorithms was investigated in order to formulate practical recommendations for selecting mobile flow route optimization algorithms depending on the size of the sensor network. A comparative analysis was performed of the exact solution of the traveling salesman problem, performed using the branch and bound method, and the approximate solution, performed using heuristic methods. To obtain an approximate solution, two heuristic algorithms were implemented: the ant colony optimization (ACO) algorithm and the simulated annealing (SA) algorithm. These algorithms were implemented for the traveling salesman problem with specific coordinates for each problem. The effectiveness of the algorithms is evaluated on networks of various sizes, from 10 to 500 nodes. The simulation results show that ACO is highly effective on small and medium-sized networks (up to 50 nodes), providing shorter routes and faster computation times. SA is determined to be the best scalable on large networks (100 nodes and more), offering stable performance under high computational load. **Conclusions.** It has been demonstrated that introducing optimization in the selection of the mobile flow route in BSM leads to a reduction in the length of the mobile flow bypass contour in the range of 30–40% depending on the network size and the distances between routers. Reducing the polling time of routers in a sensor network leads to an increase in the residual power of power supplies, and thus extends the life of the network. It has been proven that the use of heuristic algorithms is only appropriate when a high speed of calculating a new mobile flow route is required. If the speed of calculating a new route is not critical, then it is better to use accurate calculation algorithms. For each algorithm, parameters must be selected depending on the task at hand, since these parameters affect the speed of the algorithm and can reduce the range of possible routes that can be obtained during calculations. The study proves the importance of individual parameter tuning of algorithms to improve the accuracy and adaptability of solutions in mobile flow routing tasks.

Keywords: heuristic algorithms; mobile flow; optimization; traveling salesman problem; wireless sensor network.

Introduction. Analysis of recent publications

The key indicator of wireless sensor networks (WSN) that determines their practical application is their lifetime, so increasing it remains a pressing issue [1, 2]. The simplest methods for increasing the lifetime of WSNs are to improve the hardware characteristics of devices: reducing the power consumption of individual components, optimizing their placement on a chip or printed circuit board, or increasing battery capacity. Recent research in the field of miniature alternative energy converters (MEH, Micro-Energy Harvesters) has opened up a number of opportunities for creating fully autonomous sensor network nodes while maintaining their small size. There are known ready-made solutions for connecting sensor nodes to miniature solar cells, vibration energy converters, and thermogenerators based on the Peltier element [3]. However, none of the solutions for collecting and converting alternative energy has yet been widely used in real data collection networks containing hundreds of nodes. This can be explained primarily by high costs and significant expenses for regular maintenance [4].

Sensor networks are primarily designed for data collection. This means that there are one or more dedicated nodes to which information from the entire network flows. Such nodes (sinks) usually have a constant power source, interfaces for connecting to local and global networks, or more powerful computing devices. Therefore, there is a predominant direction of useful traffic in a sensor network. This results in a significantly higher volume of traffic passing through the routing nodes located near the sink. The more data

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passes through a wireless network node, the higher its power consumption. It is known that in event-driven sensor networks operating according to the asynchronous access to the transmission medium algorithm, routers are an obstacle in the life of the network. This is because in order to deliver event information in a timely manner, the router must remain in receiver mode at all times [5]. As a result, the network experiences a problem of energy consumption imbalance [6]. This leads to autonomous elements located near the central data collection node (nodes) failing earlier than others due to the discharge of their own batteries, and, as a result, the autonomous operation time of the sensor network is reduced. Various energy balancing methods are used to equalize the power consumption of all network nodes.

A promising balancing method is the use of the mobility of individual network components. Some studies [6–8] have shown that the mobility of flow can potentially provide the greatest advantage in terms of increasing the autonomous operation time of the network. In a stationary flow, it is obvious that in some areas the nodes consume almost no energy and, in the event of failure, have more than 90% of their initial energy. Even random flow movement significantly improves the distribution of residual energy. Compared to a stationary data collection node, there is a more uniform energy consumption. The paper [9] provides the following ratios: the average power of the router in transmission mode is 42 mW, the average power of the router in reception mode is 52 mW, the average power of the router in processing mode is 20 mW, and the power of the router in standby mode is 0.03 mW. The addition of a mobile node significantly reduces the power consumption of the router, as it reduces the time spent on transit transmissions. However, changing the network configuration during the information collection process leads to an increase in network latency. If the set of tasks performed by the node is not critical, there may be a decline in the quality of network service.

One way to solve this problem is to add a mobile sink, which can be an autonomous robotic system [10]. The addition of a mobile sink significantly reduces the router's energy consumption by reducing the time spent on transit transmissions. The route optimization problem can be modeled as a variant of the classic traveling salesman problem (TSP), a widely recognized combinatorial optimization problem [5]. Although exact solutions for TSP, such as those obtained using the branch and bound method, guarantee optimality, they are computationally complex for large networks, as the complexity increases factorially with the number of nodes. In scenarios where immediate and efficient solutions are required, exact algorithms may be impractical due to the high computational load. As a result, heuristic and metaheuristic approaches have gained popularity as practical alternatives, offering near-optimal solutions with significantly less computation time [11]. The article discusses the application of two heuristic algorithms – the ant colony optimization (ACO) algorithm and the simulated annealing (SA) algorithm – to solve the traveling salesman problem in the context of mobile stock route optimization. These algorithms were chosen because of their well-documented ability to perform complex optimization tasks under various constraints. The ant colony algorithm, inspired by the behavior of ants when searching for food, is known for its effectiveness in finding shorter paths in smaller networks. Annealing simulation, based on the physical process of metal annealing, offers a robust search mechanism that is suitable for complex solution spaces but typically requires more computation time than ACO.

Goals and objectives

The addition of mobile traffic can change the network configuration and, consequently, routing, leading to increased network latency. Therefore, within the scope of the study, it is necessary to select algorithms for optimizing mobile traffic routing depending on the size of the network and computational requirements. For each algorithm, parameters must be selected according to the task at hand, as these parameters affect the speed of the algorithm and can reduce the range of possible routes that can be obtained during calculations. It is important to evaluate the effectiveness of each algorithm in networks of different sizes and in conditions typical for the deployment of autonomous robotic systems. By analyzing key performance indicators such as route length, computation time, and scalability, it is necessary to determine the conditions under which each algorithm provides the best performance. The resulting metrics are intended to assist in selecting appropriate route optimization methods for autonomous robotic systems operating in real-world conditions where efficiency and adaptability are of paramount importance.

The objective of this work is to study the solution of the mobile stream route optimization problem in

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a wireless sensor network using heuristic algorithms to formulate practical recommendations for selecting mobile stream route optimization algorithms depending on the size of the sensor network.

Materials and methods

The mobile stick must survey all routers in the network only once and return to the starting point. Its route should minimize the total cost of the distance traveled. This task can be formulated as a traveling salesman problem [1].

If there are no specific requirements for the network topology, then the set of routers $N, |N| = n$, where n is the number of routers, can be considered as a set of vertices of a fully connected undirected graph of dimension n. The link of the mobile stick route between the i-th and j-th routers $(i, j) \in E,\ |E| = n^2$ will be an edge of the graph $G(N, E, C)$. The weight matrix $C = \|c_{ij}\|$ of the arcs $(i, j), (i = \overline{1, n}, j = \overline{1, n}; i \neq j)$ is known and will be called the route link cost matrix. Depending on the functionality of the network and the requirements for quality of service, the cost of a route link may vary. The article solves the problem of minimizing the length of the path traveled by the mobile flow, and the distance between routers is used as the cost of the route link. The variable of the traveling salesman problem is a Boolean variable x_{ij}, which takes the value 1 if the arc(i, j) is part of the traveling salesman's closed route, and takes the value 0 if the arc(i, j) is not part of the traveling salesman's closed route.

Then the model of the traveling salesman problem will look like this

$$Z = \min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} \qquad (1)$$

subject to such restrictions:

$$\sum_{i=1}^{n} x_{ij} = 1, \quad j = \overline{1, n}, \qquad (2)$$

$$\sum_{j=1}^{n} x_{ij} = 1, \quad i = \overline{1, n}, \qquad (3)$$

$$u_i - u_j + n x_{ij} \leq n - 1, \quad i, j = 2, \ldots, n, \quad i \neq j, \qquad (4)$$

$$u_i \geq 0, \quad i \in N \qquad (5)$$

$$x_{ij} \in \{0, 1\}, \ i = \overline{1, n}, \ \ j = \overline{1, n}. \qquad (6)$$

Constraints (2)–(5) create a so-called Hamiltonian cycle. Constraints (2) and (3) reflect the fact that the salesperson must visit each point only once. Since the graph is undirected, two constraints are necessary. Constraint (2) states that each vertex has only one incoming arc. Constraint (3) reflects the fact that each vertex has only one outgoing arc. It is necessary that the salesman's route has one cycle. This requirement is ensured by conditions (4) and (5), where u_i is the number of the step at which the i-th point is visited.

Network modeling design and configuration

Models with 10 to 500 nodes were created to simulate the conditions in which autonomous robotic systems might operate. Each node is a point of interest or a task location that the mobile stack must visit, and the distance between nodes is calculated using Euclidean metrics. Two approaches were used to distribute distances: uniform distribution (1–100 m) and normal distribution with a mathematical expectation of 5 m and a variance of 1 m^2, which allows for the simulation of different spatial configurations.

All simulations were performed in MATLAB, and each experiment was repeated 500 times to achieve statistically reliable results [12].

Implementation of algorithms

Ant-colony algorithm. ACO was implemented with parameters selected based on previous studies and adjusted for each network size:

- number of iterations: 55 for networks with 20 nodes; 3900 for networks with 50 nodes;
- ant population: 10 ants per generation;
- pheromone influence (α): 1, indicating moderate sensitivity to pheromone trails;
- heuristic influence (β): 2, emphasizing the preference for the shortest route;
- local pheromone decay (p): 0.1, decreasing the intensity of pheromones with each pass;
- global pheromone decay (e): 0.1, applied after each cycle is completed;
- selection probability (q): 0.9, which shifts the ants' selection towards optimal paths.

At each iteration, the ants independently explore routes, placing pheromones on shorter paths. Routes with

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higher pheromone concentrations become increasingly likely to be selected in subsequent iterations. The algorithm performs iterations until convergence or the maximum number of iterations is reached, after which the shortest path found is recorded.

Simulated annealing algorithm. SA was implemented using parameters related to temperature control:

- initial temperature: a value of 1000 for smaller networks and 100,000 for larger networks;
- final temperature: 0.1, which ensures gradual cooling;

cooling schedule: the temperature was reduced using an exponential decay function:

$$T_{k+1} = T_k \alpha , \qquad (7)$$

where $\alpha = 0.99$ – cooling coefficient;

- iterations: 250,000 for both network sizes to ensure the research result;
- decision-making probability function:

$$P(\Delta E) = e^{-\Delta E/T}, \qquad (8)$$

where ΔE – change in route length.

The algorithm begins by selecting a random route and sequentially explores new routes by rearranging nodes. Route changes that improve the overall length are accepted immediately, while less optimal solutions are accepted with a probability that the route length decreases in proportion to the decrease in temperature. This allows the algorithm to avoid local minima [13].

Performance indicators and their analysis

The main indicators for evaluating the performance of algorithms were:

- route length – the total distance traveled by the mobile stack to complete the route;
- computation time – the period required for the algorithm to converge to a solution;
- error rate – the percentage deviation of each heuristic solution from the known optimal route, obtained using the exact branch and bound method for smaller networks (10 and 30 nodes).

Performance indicators were analyzed for each network size, and the Robbins–Monroe procedure was used to verify the average route length values. Based on recursive estimates, ACO and SA were compared to determine the most effective algorithm depending on the network size and the required accuracy [14, 17].

Research results and their discussion

The results of this work provide insight into the comparative performance of ant colony optimization (ACO) and simulated annealing (SA) algorithms for solving the traveling salesman problem (TSP) with the aim of optimizing the route of a mobile stream. Key performance indicators, including route length, computation time, and error rate, are evaluated for networks of different sizes (10, 20, 50, 100, and 500 nodes).

Performance in small-scale networks (10 and 20 nodes)

For small networks, both ACO and SA achieved near-optimal route lengths with minimal error rates.

- Route length: ACO achieved an average route length of 357.45 units for a network with 20 nodes, outperforming SA's 367.57 units.
- Computation time: ACO demonstrated faster computation time, averaging 0.3112 s per simulation compared to 0.5230 s for SA.
- Error rate: Both algorithms had an error rate of less than 3%, with ACO recording an average error of 0.0319% and SA recording an average error of 2.8659%.

The simulation results are presented in Table 1. The minimum paths for 10 and 20 points are shown in Figures 1 and 2.

Table 1. *Modeling results for 10, 20, and 50 nodes*

№	Ant colony algorithm			Annealing simulation algorithm		
	average path length	**average time**	**mean error**	**average path length**	**average time**	**mean error**
	units	seconds	%	units	seconds	%
10 points						
1	356.900	0.5595	0	355.244	0.5595	0
20 points						
2	356.9009	0.2102	0.4662	355.2446	0.5595	0
50 points						
3	571.8715	27.1727	0.5264	572.6818	42.6522	0.6689

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These results demonstrate that ACO is more efficient for small networks, offering shorter routes and faster computation times than SA. The low error rate confirms the suitability of both algorithms for scenarios with a low number of nodes, with ACO having a slight advantage.

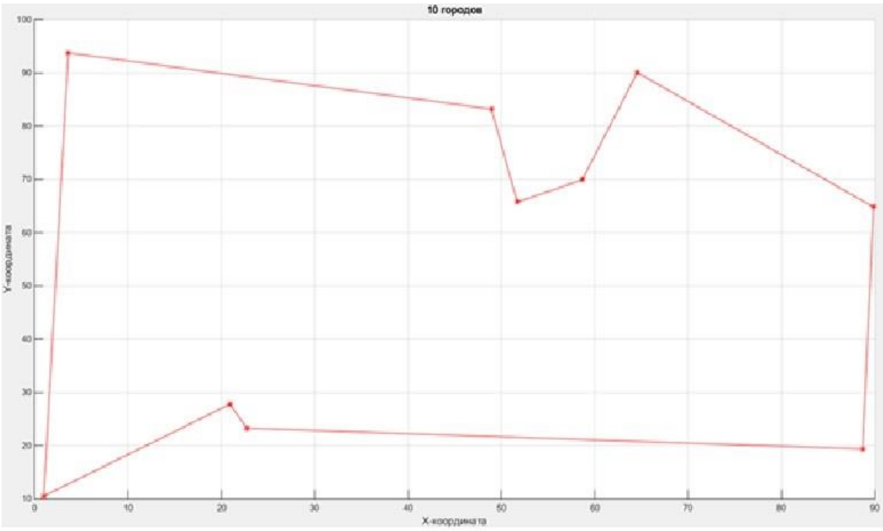

Fig. 1. Minimum route for 10 points

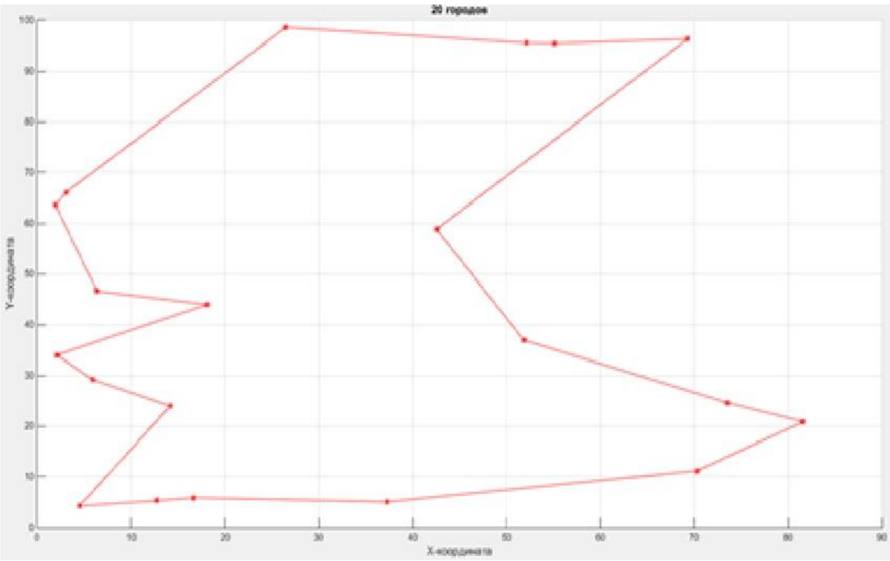

Fig. 2. Minimum route for 20 points

Productivity in medium-sized networks (50 nodes)

The simulation results are presented in Table 1. The minimum path for 50 points is shown in Figure 3.

As the network size increased to 50 nodes, ACO continued to outperform SA, although both algorithms experienced a slight increase in route length and computation time.

- Route length: ACO recorded an average length of 571.87 units, while SA created a similar but slightly longer route length of 572.68 units.
- Calculation time: ACO took 27.17 seconds, which is approximately 36% faster than the 42.65 seconds required by SA.
- Error rate: ACO maintained a low error rate of 0.5264%, while SA's error rate was 0.6689%, which is within the acceptable range for medium-sized networks.

The results show that ACO continues to be more efficient in terms of selection time for route optimization in medium-sized networks, while SA offers comparable accuracy but with higher computational costs.

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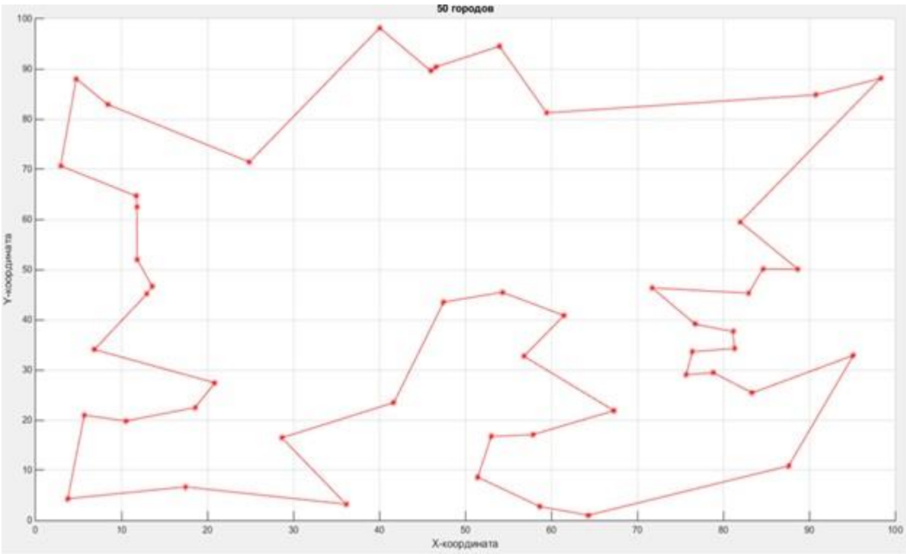

Fig. 3. Minimum route for 50 points

Performance in large-scale networks (100 and 500 nodes)

The simulation results are presented in Table 2. The minimum paths for 100 and 500 points are shown in Figures 4 and 5.

For larger networks, both algorithms encountered scalability issues, although the efficiency of ACO decreased significantly with an increase in the number of nodes [2, 14, 15].

Table 2. *Simulation results for 100 and 500 nodes*

Sample №	Ant colony algorithm		Annealing simulation algorithm	
	route length	**time**	**route length**	**time**
	units	seconds	units	seconds
100 nodes				
1	821.4988	189.513869	817.5347	42.239714
2	816.6737	186.088802	801.4941	43.638596
3	799.4715	140.772230	800.1126	48.471429
500 nodes				
1	∞	∞	1836.4	79.681766
2	∞	∞	1843.1	83.506554

1. *Network with 100 nodes*

- Route length: ACO created an average route length of 821.5 units, while SA's average route length was 817.5 units.
- Computation time: ACO dramatically increased this metric to 189.5 seconds, while SA worked faster at 42.2 seconds.
- Error rate: ACO recorded an error rate of approximately 2.6% compared to 2.3% for SA.

2. *Network with 500 nodes*

- Route length and time: Due to high computational loads, ACO's performance lagged significantly, and execution time increased non-linearly. SA, although slower than in smaller networks, was able to generate feasible solutions in a more practical time frame.

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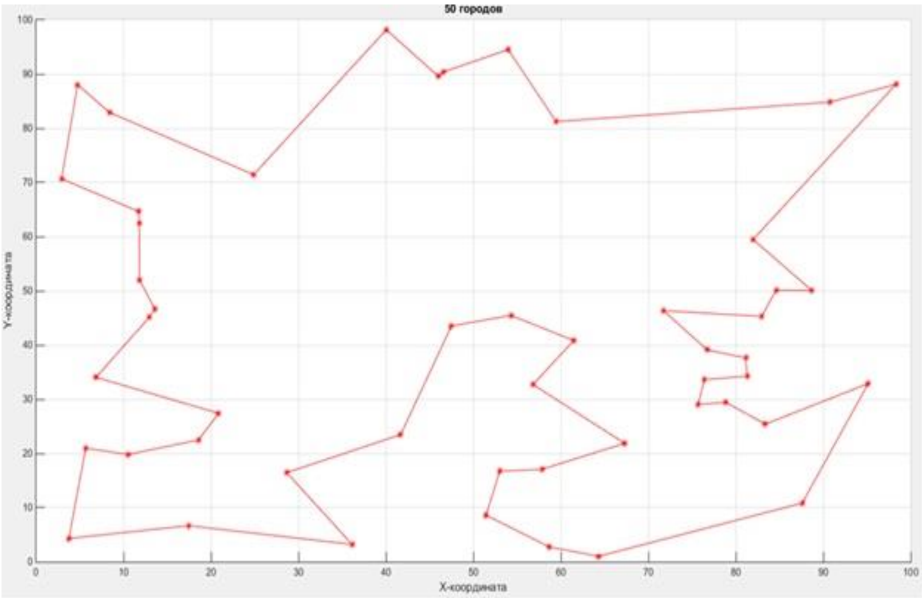

Fig. 4. Minimum route for 100 points

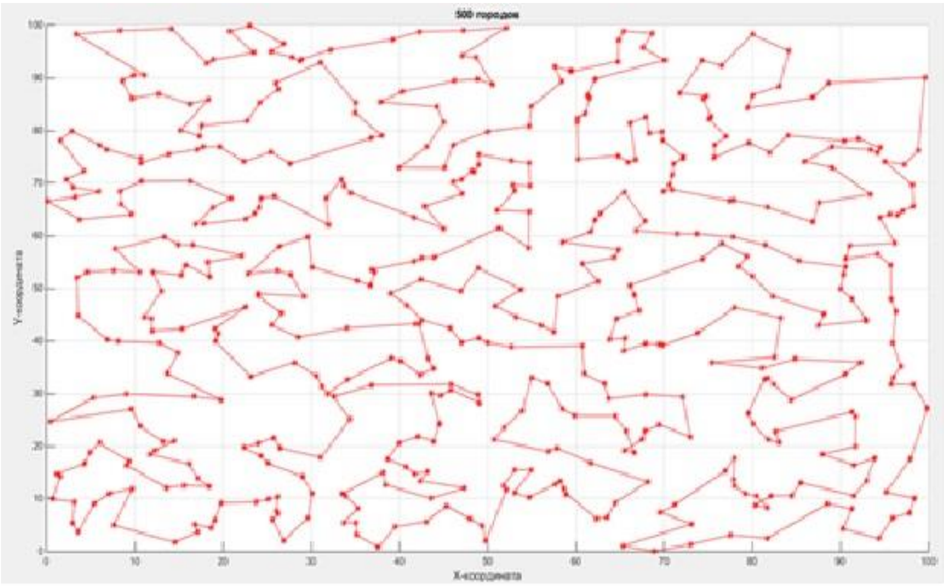

Fig. 5. Minimum route for 500 points

Brief description of algorithm productivity

The overall performance of ACO and SA for all tested network sizes indicates that ACO is better for small and medium-sized networks (up to 50 nodes) because it provides shorter routes and faster processing times. For networks with 100 nodes or more, SA becomes a significantly more scalable solution, offering more stable performance without an excessive increase in computation time.

Table 1 shows the average route lengths, computation times, and error rates for each network size and algorithm, providing a clear comparison of their suitability for different network scales.

This study contains a comparative analysis of the ant colony optimization (ACO) algorithm and the simulated annealing (SA) algorithm for solving the traveling salesman problem in the context of optimizing mobile flow routes in a wireless sensor network. The results demonstrate the advantages and disadvantages of each algorithm on networks of different sizes, providing valuable information for application in sensor networks.

The results show that ACO is very effective for small and medium-sized networks (up to 50 nodes),

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providing high route efficiency and faster convergence time compared to SA. The ability of ACO to find shorter paths with fewer iterations makes it suitable for time-sensitive applications where mobile stacks need to find optimal routes with limited computational resources.

The advantage of ACO is due to its iterative search mechanism using pheromones, which allows it to find short routes and make optimal decisions quickly. This makes it more effective for networks with a small number of nodes, where the decision space can be explored without significant computational resources.

In contrast, the simulated annealing (SA) algorithm has shown better scalability on large networks (100 nodes and more), where ACO faces a sharp increase in computation time and errors. SA uses a probabilistic decision-making mechanism that allows it to explore the solution space more broadly, avoiding premature convergence, making it suitable for complex and large networks. Although SA requires more iterations to converge on smaller networks, its performance remains stable as the network size increases, confirming the reliability of this algorithm in large environments typical of complex sensor networks.

The results obtained are consistent with previous studies, which also demonstrate the effectiveness of ACO for small, very dense networks and the performance of SA in working with larger, complex networks. Scalability confirms that the computation time for ACO increases exponentially with increasing network size, which has also been observed in similar applications.

Based on these results, practical recommendations can be formulated for selecting mobile sink route optimization algorithms depending on the size of the sensor network. In cases where the mobile stream polls a limited number of sensors and conditions require frequent route recalculations (e.g., rapid response sensor networks for emergency services, fire departments, or medical services), then the faster convergence of ACO is a significant advantage [13, 15]. For navigation tasks in large-scale environments, such as surveillance systems, the scalability of SA ensures reliable performance, allowing routes to be calculated in a reasonable time even with a high level of network complexity.

The main limitation of this study is the use of modeling that does not take into account dynamic environmental factors that can affect mobile stream navigation in real-world conditions. Future work plans to add adaptive real-time algorithms to account for changing obstacles or operational constraints. In addition, hybrid approaches can be developed that combine the fast convergence of ACO with the broader search capabilities of SA to optimize both computational efficiency and reliability of solutions in networks of various scales.

Conclusions and prospects for further research

An evaluation and comparative analysis of the performance of the ant colony optimization (ACO) algorithm and the simulated annealing (SA) algorithm for solving the traveling salesman problem in mobile flow route optimization tasks in wireless sensor networks has been performed. The results demonstrate that ACO is effective for small and medium-sized networks, where it provides shorter routes and faster computation times compared to SA.

For large networks (100 nodes and more), SA has demonstrated the ability to provide acceptable solutions within practical time constraints. This makes it suitable for complex environments where autonomous robotic systems need to navigate large spatial structures or dynamically respond to changing route requirements.

The results of the study offer guidelines for selecting mobile stream route optimization algorithms depending on network size and computational requirements.

Promising areas of research may include the development of hybrid approaches that combine the advantages of ACO and SA to improve both efficiency and scalability [16]. In addition, the implementation of these algorithms in real sensor networks could provide practical information about their effectiveness in dynamic conditions, which will help to further refine their use in robotic navigation and route planning tasks.

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ОПТИМІЗАЦІЯ МАРШРУТУ МОБІЛЬНОГО СТОКУ В БЕЗДРОТОВІЙ СЕНСОРНІЙ МЕРЕЖІ З ВИКОРИСТАННЯМ ЕВРИСТИЧНИХ АЛГОРИТМІВ

Предметом дослідження є бездротова сенсорна мережа (БСМ) з мобільним стоком. **Мета роботи** – підвищити працездатність БСМ, збільшити тривалість її життя та функціювання завдяки зменшенню часу затримки передачі даних у процесі опитування маршрутизаторів унаслідок оптимізації маршруту мобільного стоку способом обрання найбільш ефективного алгоритму. Для досягнення окресленої мети необхідно виконати такі **завдання**: оптимізувати маршрут мобільного стоку БСМ за допомогою розв'язання задачі комівояжера методом гілок і меж та порівняння умовної середньої довжини маршруту множини рішень без оптимізації та з оптимізацією за допомогою процедури Роббінса – Монро; провести порівняльний аналіз точного розв'язку задачі комівояжера, отриманого методом гілок і меж, і наближеного рішення, отриманого евристичними методами; сформулювати практичні рекомендації щодо вибору алгоритмів оптимізації маршруту мобільного стоку залежно від розміру сенсорної мережі. Застосовано такі **методи:** імітаційне моделювання, методи оптимізації, математичне оброблення даних. **Досягнуті результати.** Досліджено розв'язання задачі оптимізації маршруту мобільного стоку в БСМ з використанням евристичних алгоритмів з метою формулювання практичних рекомендації щодо вибору алгоритмів оптимізації маршруту мобільного стоку залежно від розміру сенсорної мережі. Проведено порівняльний аналіз точного розв'язку задачі комівояжера, виконаного методом гілок і меж, і наближеного рішення, виконаного евристичними методами. Для отримання наближеного рішення реалізовано два евристичні алгоритми: мурашиний алгоритм (ACO) і алгоритм імітації відпалу (SA). Зазначені алгоритми було реалізовано для задачі комівояжера з конкретними координатами для кожної задачі. Ефективність алгоритмів оцінюється на мережах різного масштабу – від 10 до 500 вузлів. Результати моделювання демонструють, що ACO має високу ефективність на малих і середніх мережах (до 50 вузлів), забезпечуючи більш короткі маршрути та швидкий час обчислень. SA визначається кращою масштабованістю на великих мережах (100 вузлів і більше), пропонуючи стабільну продуктивність за високого обчислювального навантаження. **Висновки.** Продемонстровано, що введення оптимізації у виборі маршруту мобільного стоку в БСМ приводить до зменшення довжини контуру обходу мобільного стоку в діапазоні 30–40% залежно від розмірності мережі та відстаней між маршрутизаторами. Скорочення часу опитування маршрутизаторів у сенсорній мережі сприяє збільшенню залишкової потужності блоків живлення, а отже, продовжує тривалість життя мережі. Доведено, що використання евристичних алгоритмів доцільне тільки тоді, коли необхідна висока швидкість розрахунку нового маршруту мобільного стоку. Якщо швидкість розрахунку нового маршруту не є критичною, тоді краще використовувати точні алгоритми обчислення. Для кожного алгоритму потрібно підбирати параметри залежно від поставленого завдання, оскільки ці параметри впливають на швидкість роботи алгоритму й здатні зменшити діапазон можливих маршрутів, які можна отримати внаслідок розрахунків. Дослідження доводить значущість індивідуального налаштування параметрів алгоритмів для підвищення точності й адаптивності рішень у задачах маршрутизації мобільного стоку.

Ключові слова: евристичні алгоритми; мобільний стік; оптимізація; задача комівояжера; бездротова сенсорна мережа.

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