ДОДАТОК А

Звіт результатів перевірки на унікальність тексту в базі ХНУРЕ

UNICHECK
by Turnitin

Ім'я користувача:
Кардаш Євген Вікторович каф.ПІ

ID перевірки:
1016296279

Дата перевірки:
30.05.2024 02:35:50 EEST

Тип перевірки:
Doc vs Internet + Library

Дата звіту:
30.05.2024 09:38:29 EEST

ID користувача:
100013622

Назва документа: 2023_ПІ_ТП_ІПЗм_22_2_Шемрікович_А_Д_скорочений

Кількість сторінок: 44 Кількість слів: 7204 Кількість символів: 58360 Розмір файлу: 1.14 MB ID файлу: 1016091000

Виявлено модифікації тексту (можуть впливати на відсоток схожості)

0.36%
Схожість

Найбільша схожість: 0.12% з Інтернет-джерелом (http://dspace.snu.edu.ua:8080/jspui/bitstream/123456789/523/1/tech_2

0.24% Джерела з Інтернету | 31 .... Сторінка 46

0.12% Джерела з Бібліотеки | 5 .... Сторінка 46

0% Цитат

Вилучення цитат вимкнене

Вилучення списку бібліографічних посилань вимкнене

0%
Вилучень

Немає вилучених джерел

Модифікації

Виявлено модифікації тексту. Детальна інформація доступна в онлайн-звіті.

Підозріле форматування | 13 сторінок

Рисунок А.1 – Результат перевірки кваліфікаційної роботи бакалавра на плагіат

ДОДАТОК Б

Слайди презентації

Рисунок Б.1 – Слайд 1

Рисунок Б.2 – Слайд 2

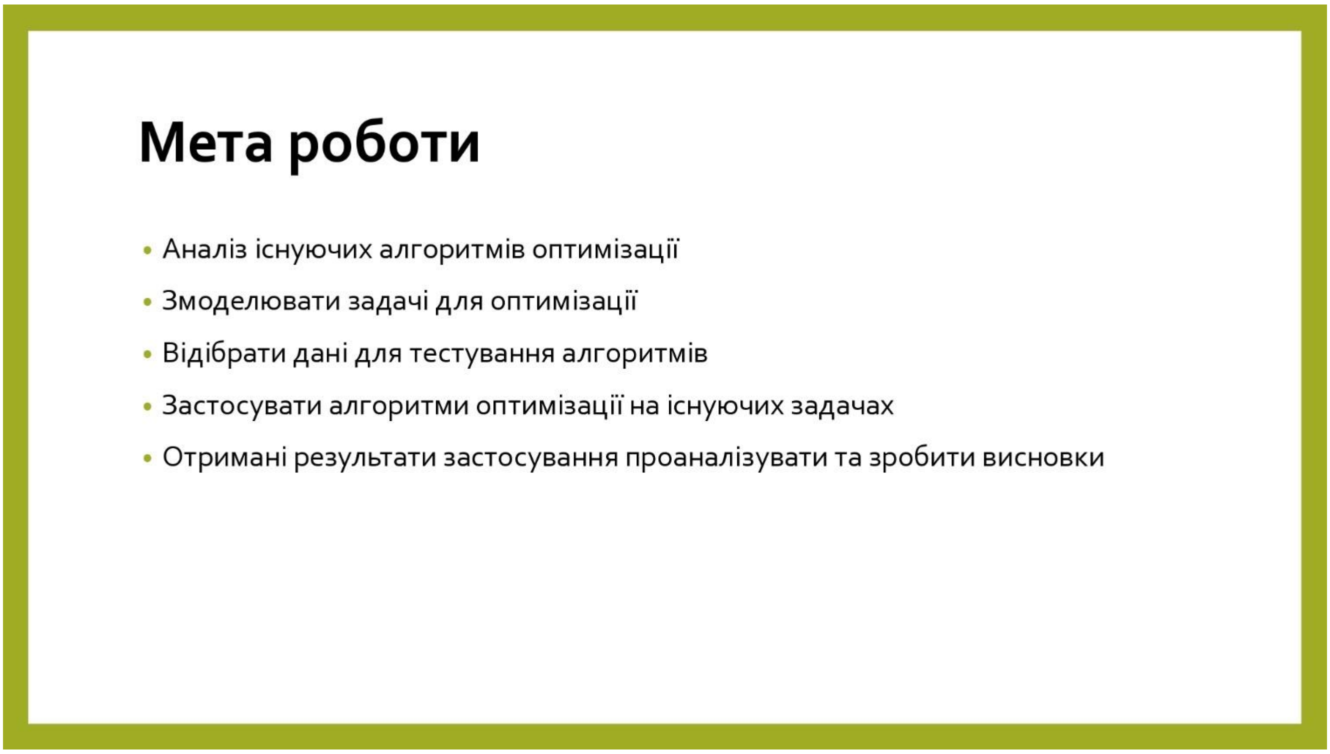

Рисунок Б.3 – Слайд 3

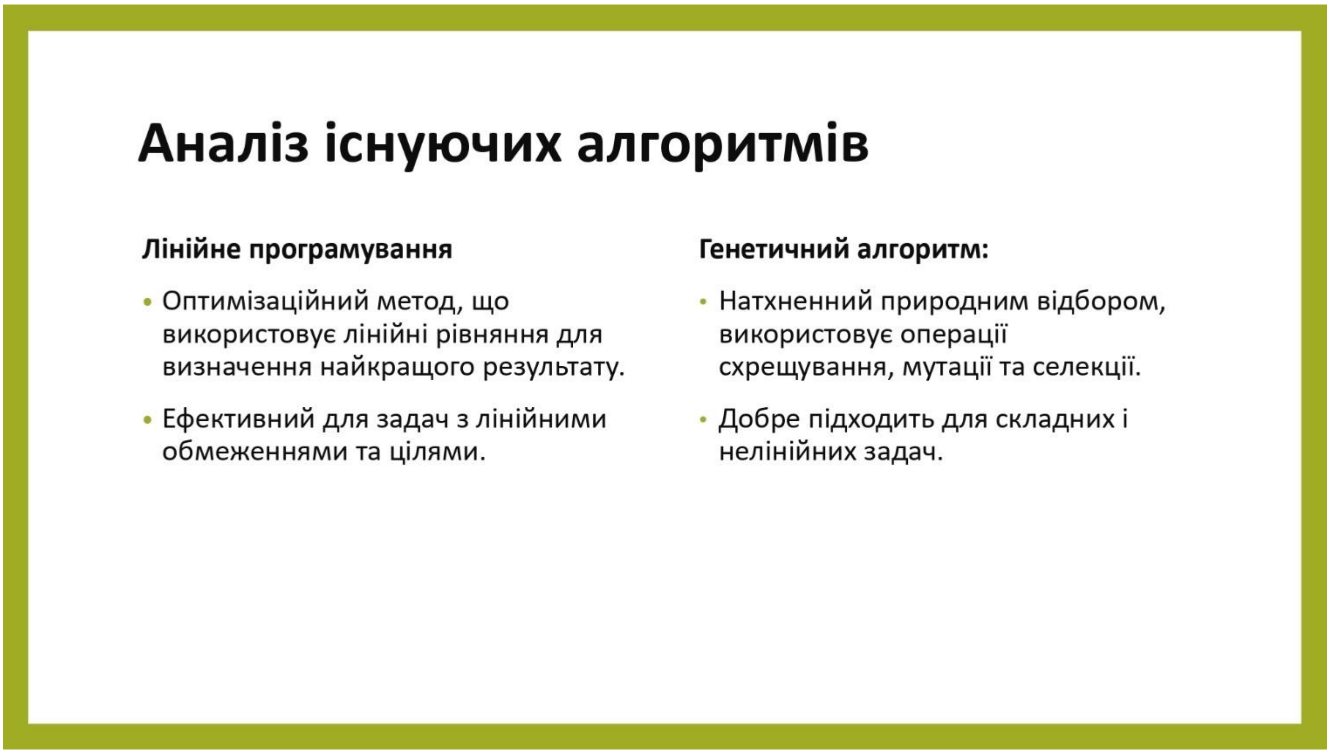

Рисунок Б.4 – Слайд 4

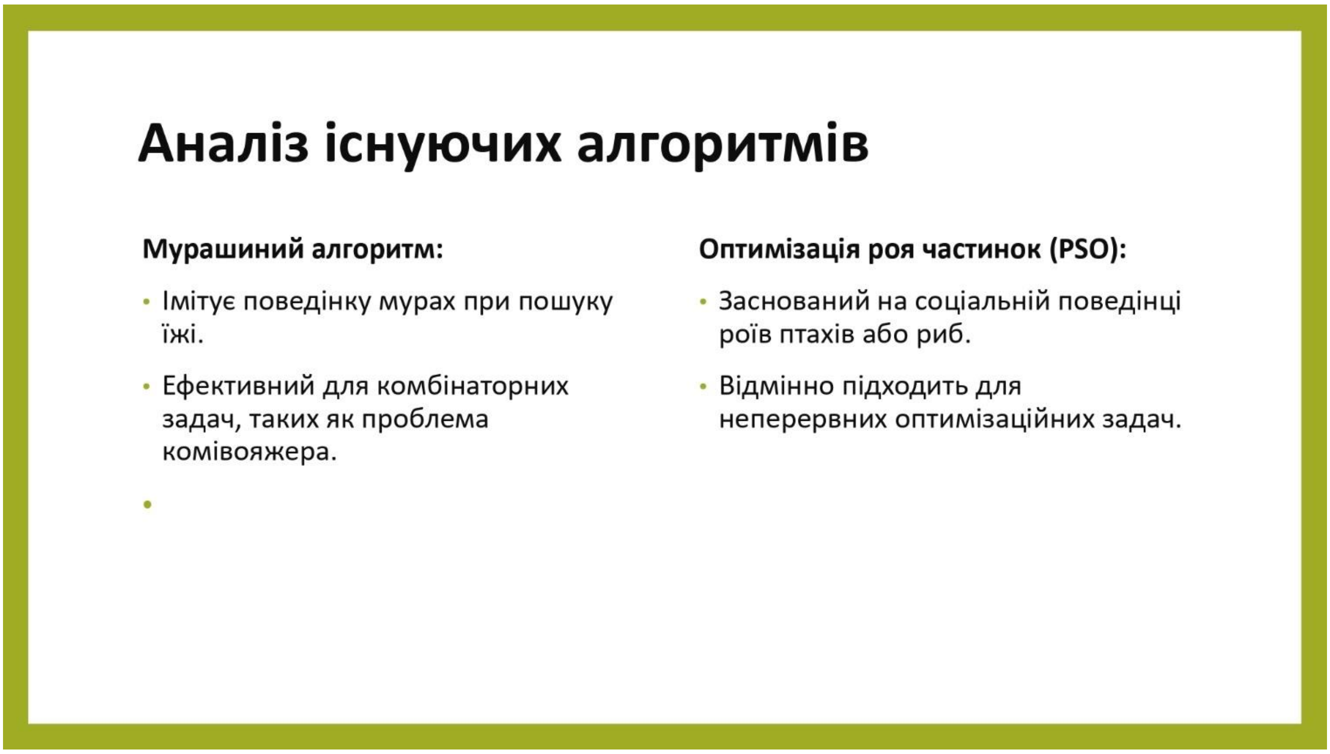

Рисунок Б.5 – Слайд 5

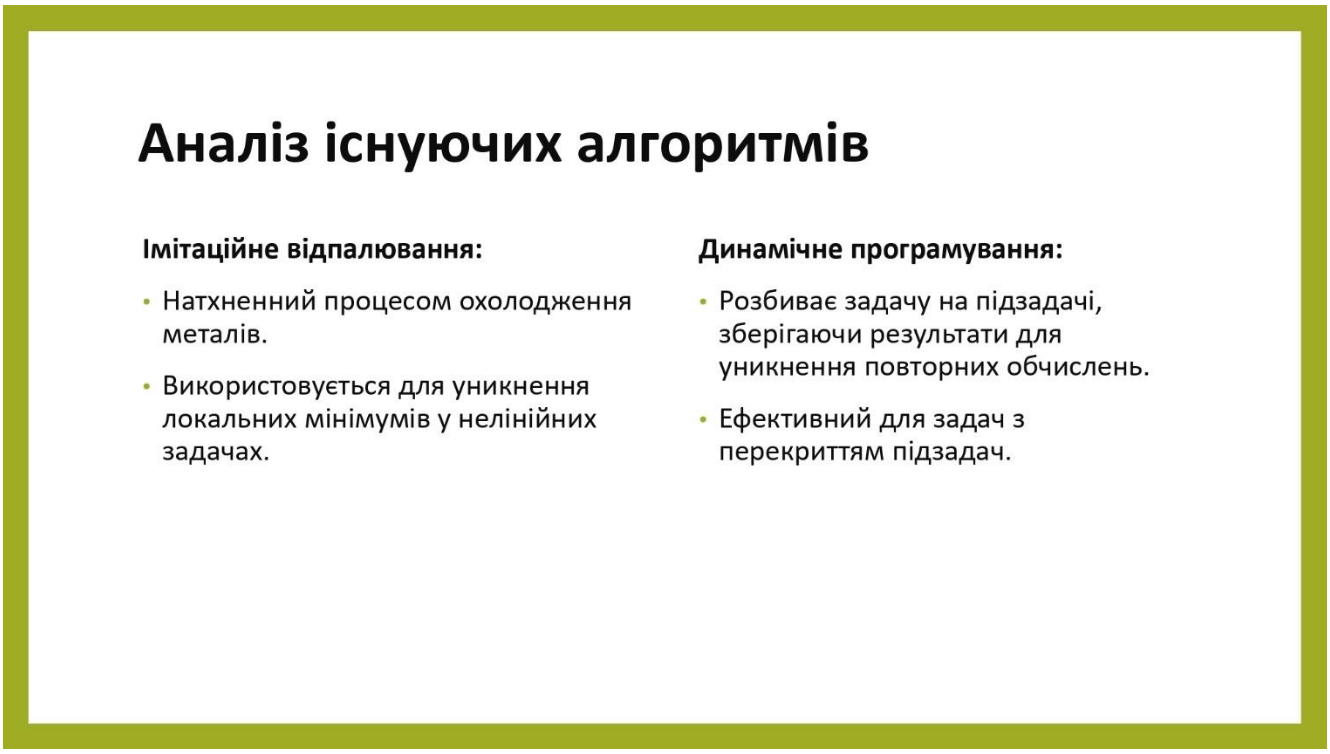

Рисунок Б.6 – Слайд 6

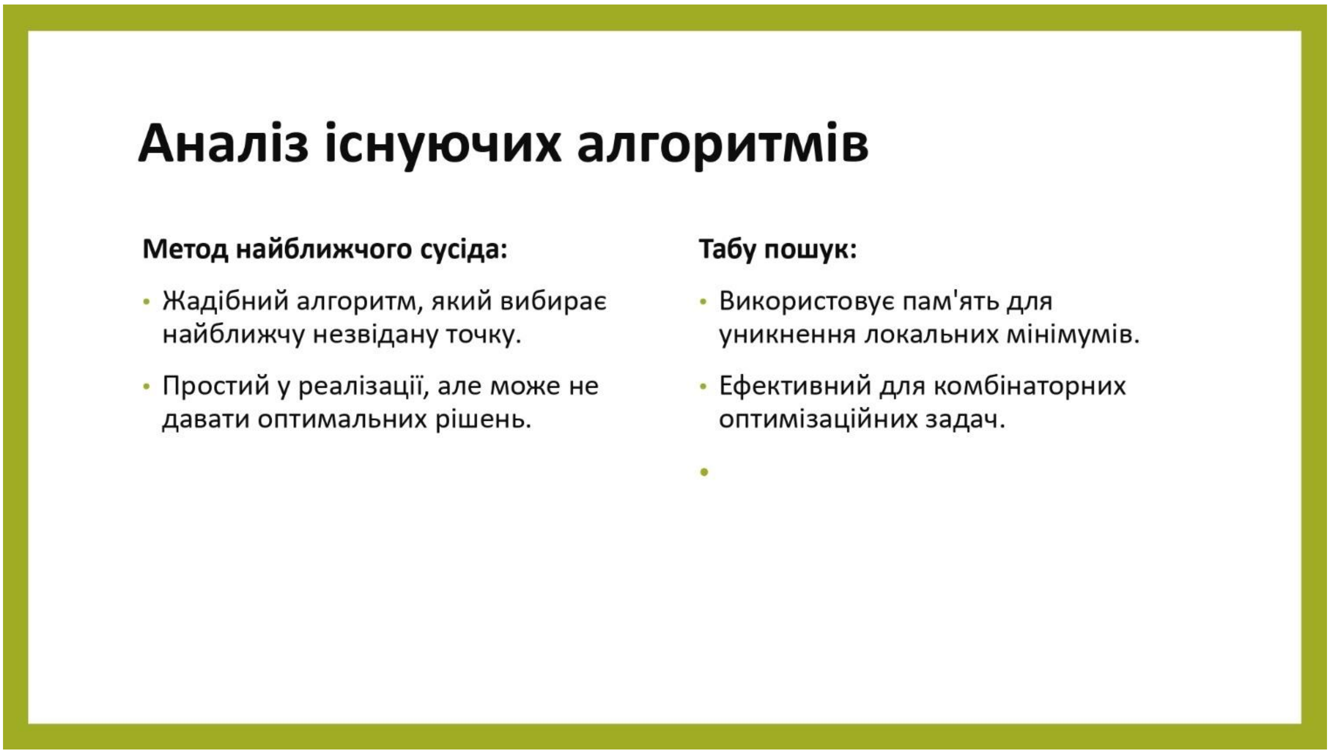

Рисунок Б.7 – Слайд 7

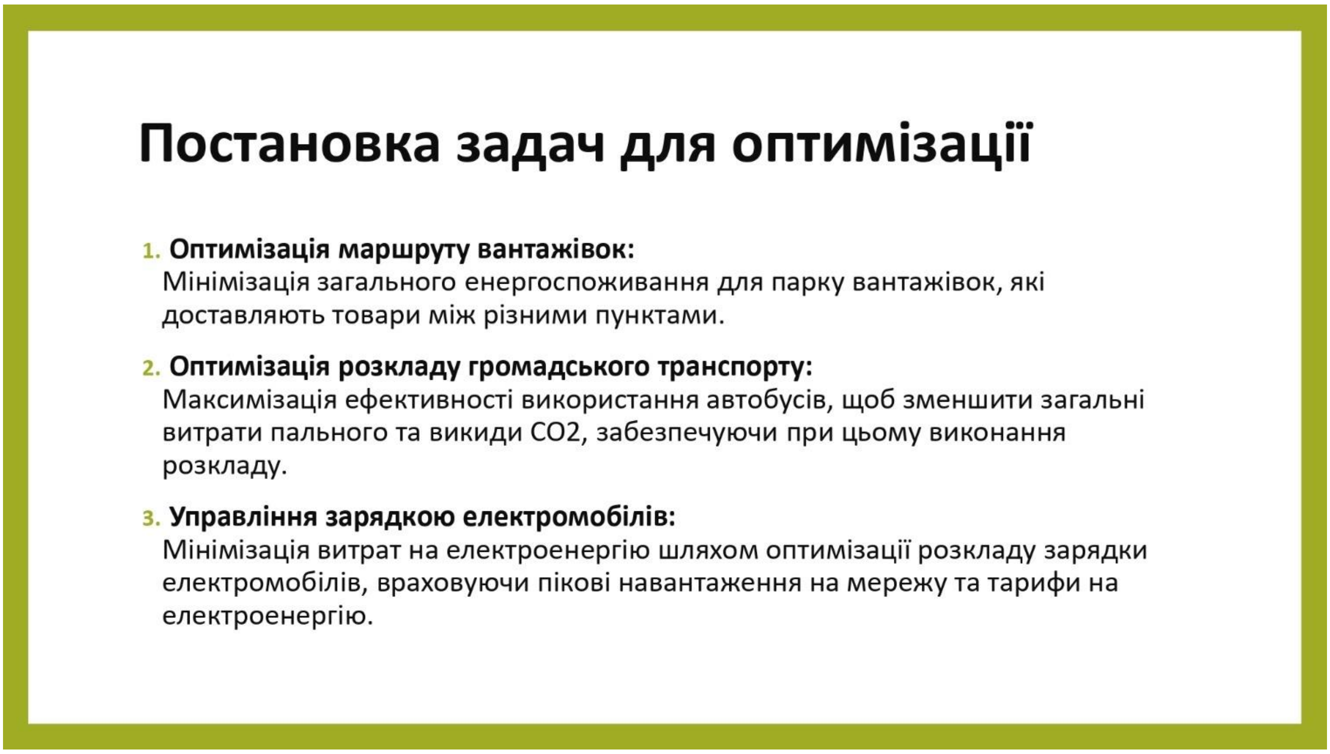

Рисунок Б.8 – Слайд 8

Рисунок Б.9 – Слайд 9

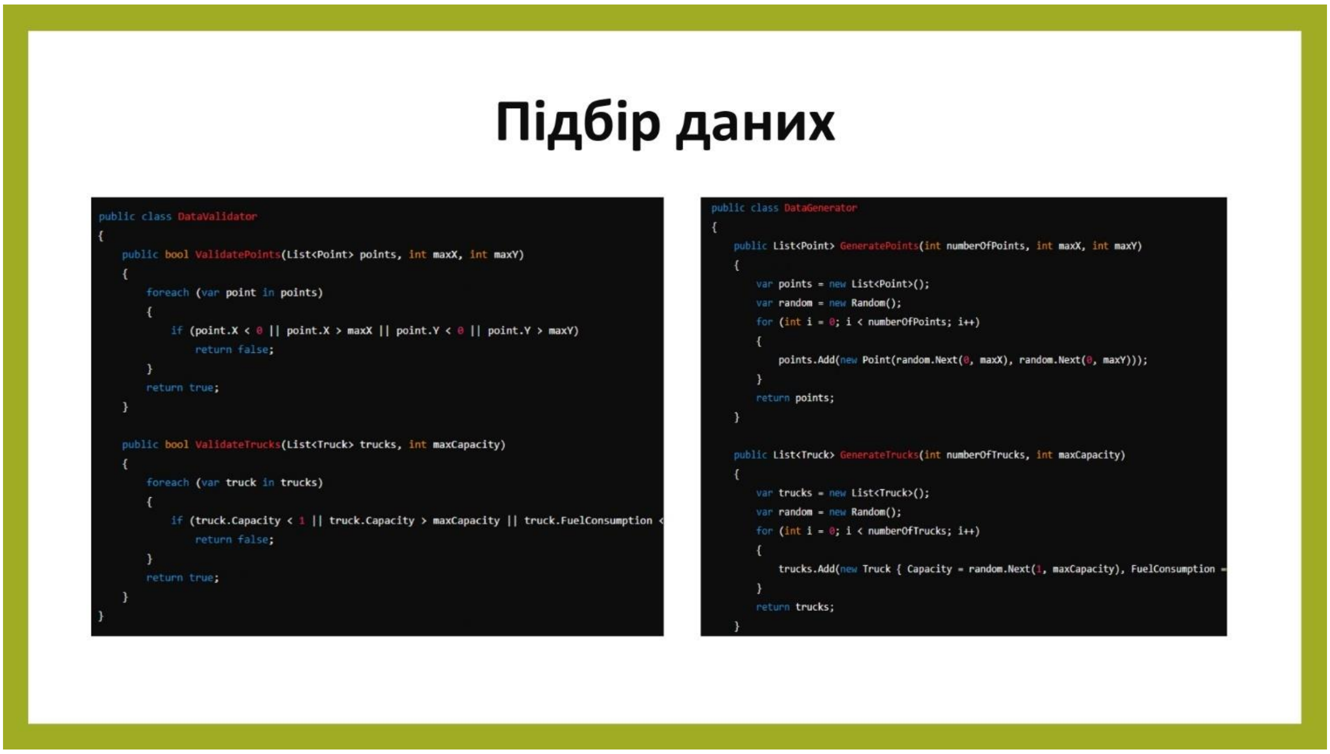

Рисунок Б.10 – Слайд 10

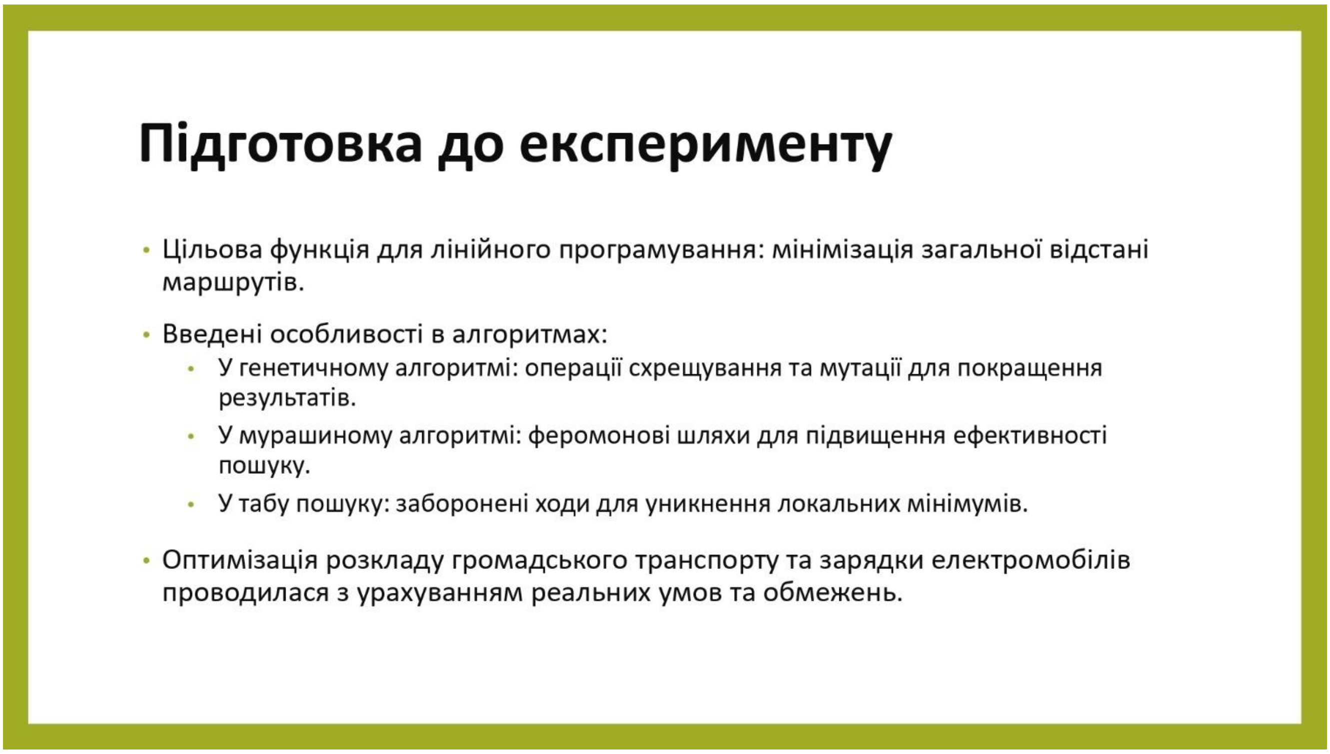

Рисунок Б.11 – Слайд 11

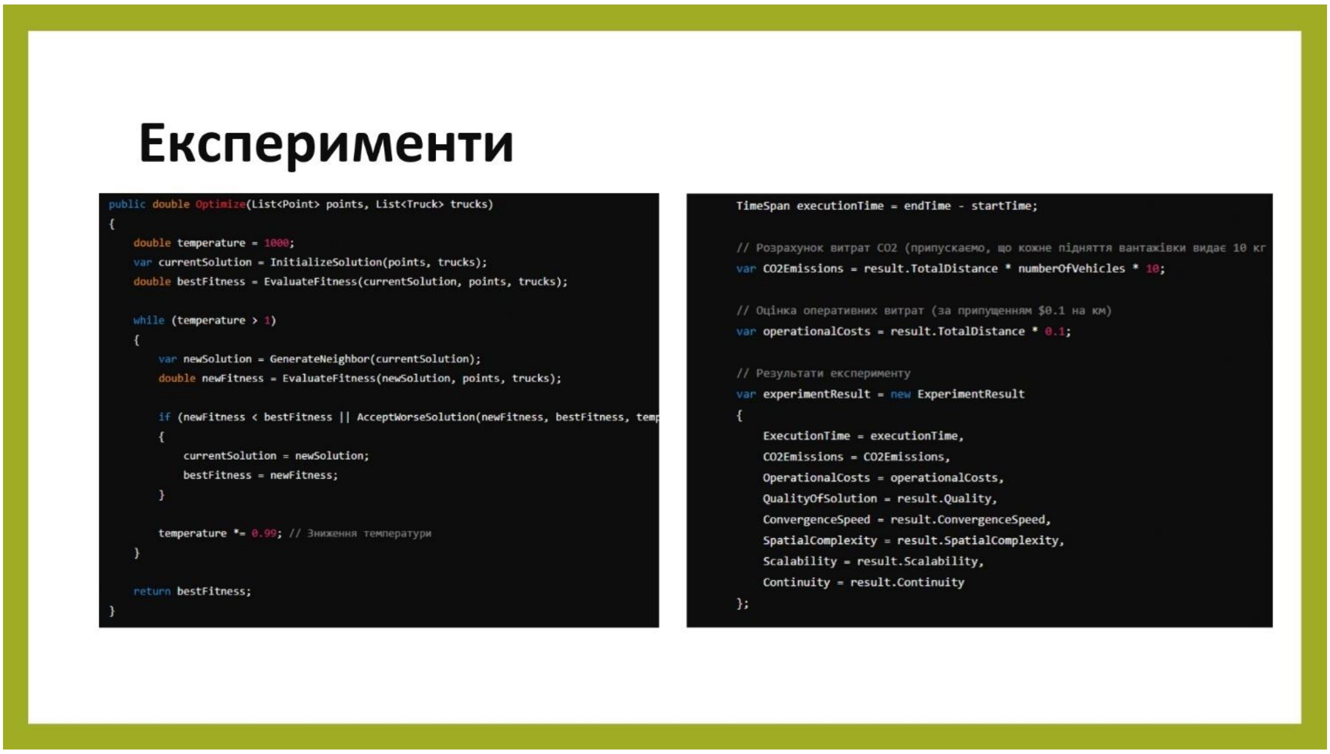

Рисунок Б.12 – Слайд 12

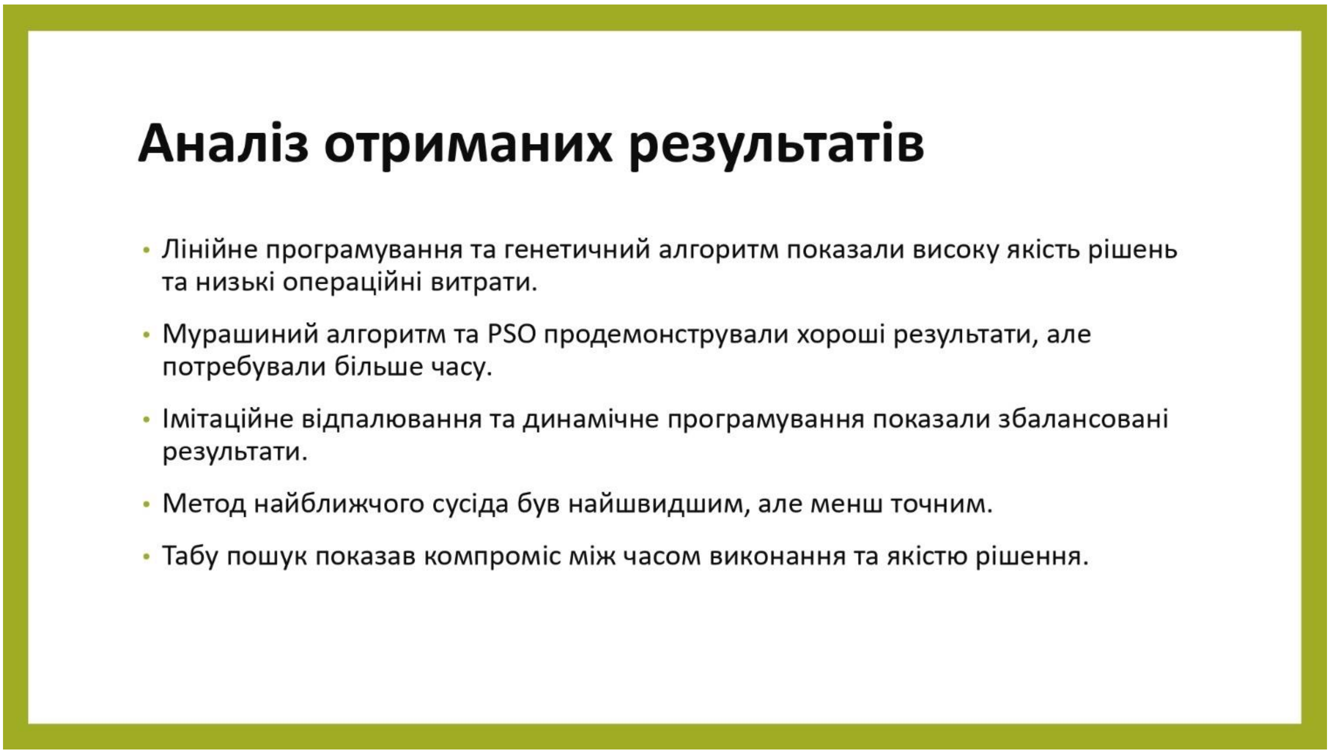

Рисунок Б.13 – Слайд 13

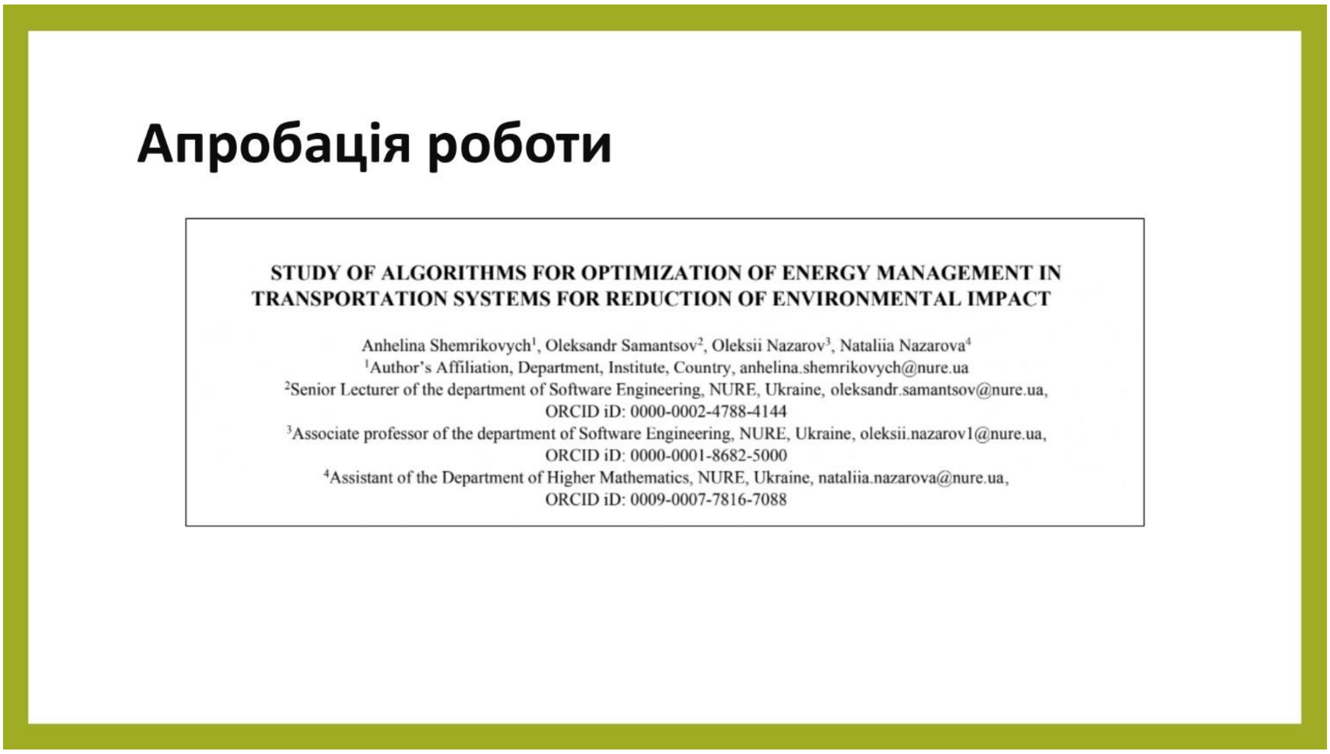

Рисунок Б.14 – Слайд 14

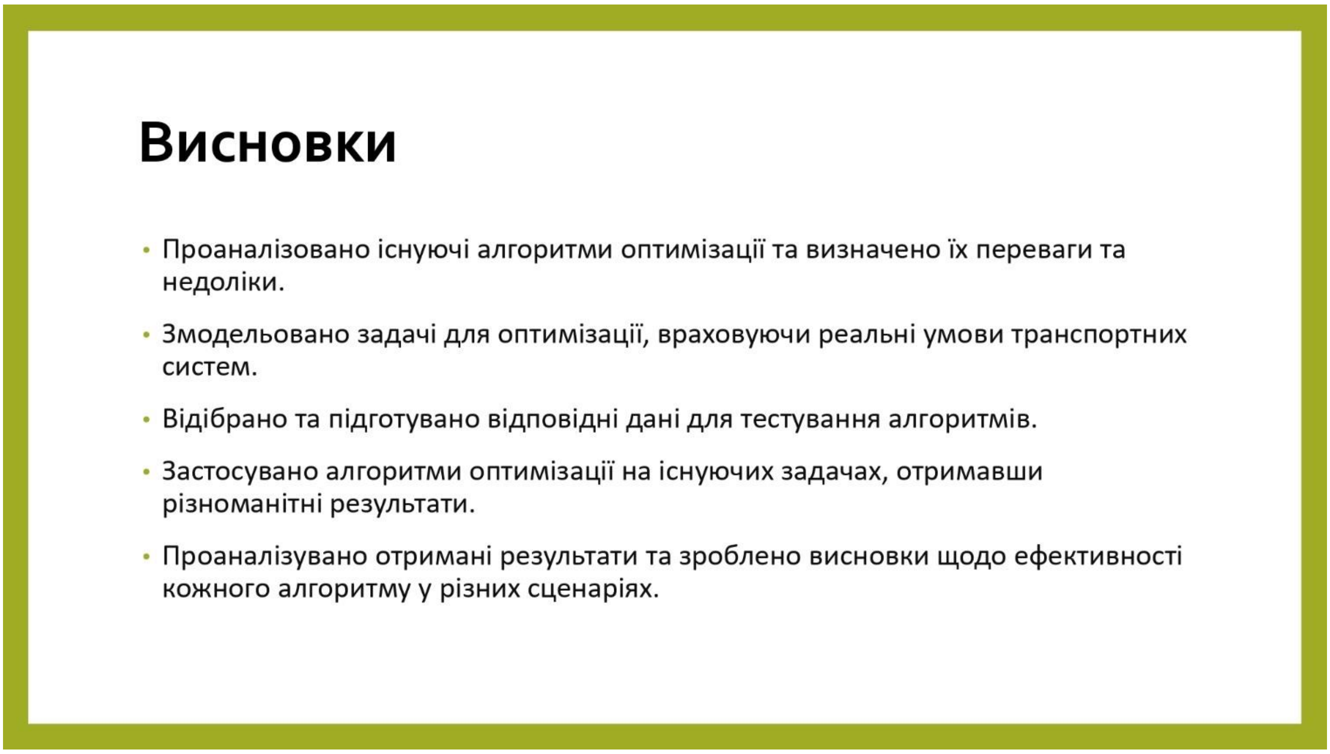

Рисунок Б.15 – Слайд 15

ДОДАТОК В

Апробація результатів роботи

STUDY OF ALGORITHMS FOR OPTIMIZATION OF ENERGY MANAGEMENT IN TRANSPORTATION SYSTEMS FOR REDUCTION OF ENVIRONMENTAL IMPACT

Anhelina Shemrikovych[1], Oleksandr Samantsov[2], Oleksii Nazarov[3], Nataliia Nazarova[4]
[1]Author's Affiliation, Department, Institute, Country, anhelina.shemrikovych@nure.ua
[2]Senior Lecturer of the department of Software Engineering, NURE, Ukraine, oleksandr.samantsov@nure.ua,
ORCID iD: 0000-0002-4788-4144
[3]Associate professor of the department of Software Engineering, NURE, Ukraine, oleksii.nazarov1@nure.ua,
ORCID iD: 0000-0001-8682-5000
[4]Assistant of the Department of Higher Mathematics, NURE, Ukraine, nataliia.nazarova@nure.ua,
ORCID iD: 0009-0007-7816-7088

The object of the research is the technology of optimization algorithms for energy consumption management in transport systems. The purpose of the work is research and analysis of the effectiveness of optimization algorithms for the purpose of reducing environmental impact, selection of criteria and methods for comparative analysis. As a result of the work, the existing algorithms for optimizing energy consumption management in transport systems were considered, their features, advantages and disadvantages and principles of operation were investigated, methods of comparison were described and demonstrated, and formulas for calculating numerical indicators were proposed.
TRANSPORT SYSTEMS, OPTIMIZATION ALGORITHMS, ENERGY MANAGEMENT, ECO-FRIENDLY ALGORITHMS.

Об'єктом дослідження є технології алгоритмів оптимізації керування енергоспоживанням у транспортних системах. Метою роботи є дослідження та аналіз ефективності алгоритмів оптимізації з метою зменшення екологічного впливу, виділення критеріїв та методів для проведення порівняльного аналізу. У результаті роботи розглянуто існуючі алгоритми оптимізації керування енергоспоживанням у транспортних системах, досліджено їх особливості, переваги та недоліки та принципи роботи, описано та продемонстровано методи порівняння та запропоновано формули для обчислення числових показників.
ТРАНСПОРТНІ СИСТЕМИ, АЛГОРИТМИ ОПТИМІЗАЦІЇ, ЕНЕРГОМЕНЕДЖМЕНТ, ЕКОЛОГІЧНО ЧИСТІ АЛГОРИТМИ.

1. Introduction

In the intricate tapestry of our modern world, the veins of trade and communication are intricately woven through maritime and road transportation systems. While these arteries of trade and mobility are essential to global prosperity, they also carry a burden of environmental impact.

The constant demand for movement, whether of goods or people, has cast a deep shadow on our planet, manifesting itself in the rapid growth of carbon emissions and a significant environmental burden.

The specter of climate change looms, demanding a reassessment of how we move around our planet. The oceans teem with ships carrying goods across continents, and the roads pulse with vehicles carrying people and goods. But the fuel that powers these journeys is often too costly for our environment.

This study examines algorithms for optimizing energy management in transportation systems from an environmental impact perspective.

The analysis derives the main evaluation criteria and forms a comparison model.

The goal of this work is to identify methodologies that minimize energy consumption without compromising the integrity of transportation systems.

In order to get a result that would satisfy the goal, it is necessary to solve a series of the following problems:

- analyze existing energy management optimization algorithms;
- determine the methods and criteria for comparing algorithms;
- model the conditions for conducting experiments to evaluate the algorithms;
- use the obtained data to measure the selected metrics for comparing algorithms;
- analyze the results obtained;
- formulate recommendations for the use of the algorithms;
- propose a possible extension of the study and characterize the relevance of the work in the future.

The subject of the study is the effectiveness and feasibility of using algorithms to optimize energy management in transportation systems in terms of environmental impact.

The subject of the study are algorithms for optimization of energy management.

The research methods are measurement of performance indicators by criteria and their calculation using the proposed mathematical formulas for calculating each of the indicators.

The results of the study can be successfully used in the creation or further analysis of new algorithms for optimization of energy management, or in the selection of the most optimal algorithm under existing conditions.

Рисунок В.1 – Сторінка 1

2. Analysis of the subject area

Gasoline, the quintessential energy source for marine and road transportation, is the cornerstone of global mobility. But behind its ubiquitous role lies a shadow - a history of environmental impacts that reverberate across oceans and urban landscapes.

In maritime trade and transportation, gasoline takes its place among a variety of fuels. While it contributes to the energy needs of ships, its environmental impact requires careful consideration. While gasoline-powered ships emit relatively low levels of sulfur oxides (SOx) and particulate matter, they contribute to the global greenhouse gas burden. Burning gasoline releases carbon dioxide (CO_2), adding to the complex matrix of marine emissions that affect the climate and the delicate balance of marine ecosystems.

Next, let's talk about gasoline in automobiles. The history of gasoline's impact on road transportation is similar to its role at sea. As the primary fuel for internal combustion engines in cars, trucks and buses, gasoline plays a key role in ensuring mobility. But that confidence comes at a price. Gasoline-powered vehicles contribute significantly to urban air pollution by emitting nitrogen oxides (NOx) and volatile organic compounds (VOCs). These emissions not only degrade air quality, but also contribute to respiratory health problems, especially in densely populated urban areas.

Next, the cumulative impact. The cumulative environmental impact of both marine and road transport fuels transcends geographic boundaries. While road transport typically affects local air quality, maritime transport extends its impact over large expanses of water, affecting coastal regions and the high seas. The cumulative emissions of CO_2, methane, NOx and other pollutants paint a grim picture - a story of environmental impact that goes beyond the convenience and necessity of transportation.

On to mitigation and solutions. Tackling the pollution caused by the use of gasoline in transportation requires a multi-pronged approach. Tighter regulations enforce emissions standards and encourage the development of cleaner engine technologies. The transition to electric vehicles, hybrid systems, and research into sustainable alternative fuels offer a glimmer of hope for reducing the environmental impact of gasoline. Innovations in engine efficiency and emissions control offer promising ways to reduce pollution while maintaining mobility.

Finally, the balance between mobility and responsibility. Gasoline, an indispensable energy source, requires a delicate balance between progress and environmental stewardship. As we move toward a transportation-dependent future, the imperative is not to deny mobility, but to innovate greener solutions. Using cleaner fuels, improving engine technology, and fostering a collective commitment to reducing our dependence on gasoline are important steps toward a harmonious coexistence of mobility and environmental responsibility. This balance holds the promise of a cleaner and healthier planet for future generations.

Environmental Impact Metrics	Marine Transport (per year)	Auto Transport (per year)
Carbon Dioxide (CO_2) Emissions	120 million tons	420 million tons
Sulfur Oxides (SOx) Emissions	5,000 tons	2,000 tons
Particulate Matter (PM) Emissions	300 tons	1,500 tons
Nitrogen Oxides (NOx) Emissions	2,000 tons	6,000 tons
Volatile Organic Compounds (VOCs)	150 tons	300 tons

3. Problem statement

After analyzing the subject industry, its main needs and existing problems, it is necessary to analyze what algorithms exist for optimizing energy management and formulate criteria for evaluating these algorithms.

Possible criteria for evaluating the performance of each algorithm may include:

- Energy savings. The effectiveness of the algorithm in conserving energy while maintaining or improving performance, and the ability of the algorithm to minimize fuel consumption during transport operations;

- Environmental Impact Reduction. The ability of the algorithm to reduce greenhouse gas emissions (CO_2, NOx, SOx, VOCs) associated with transportation activities, and the impact of the algorithm on reducing pollutants that contribute to air and water pollution; - Operational Performance. How efficiently the algorithm uses resources, improving vehicle/ship performance while reducing energy consumption;

- Scalability and adaptability. How well the algorithm performs when applied to different scales of transportation systems, from individual vehicles/ships to entire fleets, the performance of the algorithm under different conditions, including weather, traffic, and work shifts;

- Real-time implementation. The speed of the algorithm to provide optimized solutions for dynamic changes in the environment and operations;

- Computational requirements of the algorithm for real-time implementation in transportation systems.

- Economic Efficiency. Costs associated with implementing and supporting the algorithm in transportation systems, ability of the algorithm to provide significant environmental benefits compared to the cost of implementation;

- Durability and reliability. Resilience of the algorithm to uncertainties and unexpected scenarios in transportation operations, consistency and accuracy of the algorithm to provide optimized solutions over time;

- Compliance with regulatory requirements. The extent to which the algorithm helps transportation systems meet environmental and emissions standards;

- Ease of use and integration. Ease of integration of the algorithm into existing transportation systems;

- User Adaptability. Convenience of the algorithm for transport operators and decision makers.

Рисунок В.2 – Сторінка 2

Taking into account all of the above criteria and analyzing the subject area, the following tasks need to be solved as part of the study of algorithms for optimizing energy management in transportation systems to reduce environmental impact:

- Review existing algorithms for optimizing energy management in transportation systems,

- Select those that can be used to reduce environmental impact;

- Prioritize the above evaluation criteria;

- Analyze and organize the algorithms according to the above evaluation criteria;

- Formulate an experimental plan to obtain experimental data, create software test environments for measurements for each of the criteria and algorithms;

- Conduct the experiment, analyze the results, and document the results;

- Provide recommendations and analysis results for the use of specific energy management optimization algorithms.

4. Overview of the main algorithms used for optimization

These optimization algorithms offer a variety of approaches to managing energy consumption in transportation systems, providing solutions for route optimization, resource allocation, vehicle scheduling, and energy efficient operation. Each algorithm has its own strengths and applications, and their choice often depends on the specific needs and constraints of the transportation context.

The most commonly used algorithms are:

Linear Programming. Used in route optimization, resource allocation, and planning in transportation systems. It aims to maximize or minimize a linear objective function subject to linear constraints. It is used to optimize transportation logistics and distribution.

Genetic Algorithms (GA). Used in vehicle routing, fleet optimization, and energy-efficient vehicle design. GA mimics the processes of natural selection to constantly evolve solutions. This is important for finding optimal solutions to complex transportation and logistics problems.

Ant Colony Optimization (ACO). Used to find the shortest routes in transportation networks and optimize traffic flow. ACO simulates the behavior of ants foraging for food and guides algorithms to find optimal routes and paths. It is effective in solving routing and resource allocation problems.

Particle Swarm Optimization (PSO). Used in route optimization search, vehicle scheduling, and energy-efficient vehicle routing. PSO models the social behavior of organisms by iteratively optimizing possible solutions. It is useful for solving complex optimization problems in transportation systems.

Heating Simulation. Used in vehicle routing, energy efficient routing, and scheduling. Simulated annealing mimics the annealing process in metallurgy to find optimal solutions by taking worse solutions first before approaching the optimal one.

Dynamic Programming. Used for optimal control of vehicle operation and energy-efficient routing. Dynamic programming breaks down complex problems into simpler subproblems that are suitable for finding optimal solutions over time, such as in route planning and energy management.

Heuristic Algorithms. Used in vehicle routing, traffic flow optimization, and fleet management. Heuristic algorithms, including methods such as nearest neighbor, insertion, and expansion, provide approximate solutions to transportation optimization problems.

Metaheuristic algorithms. Used in vehicle scheduling, energy-efficient routing, and fleet optimization. Metaheuristic algorithms include a variety of methods such as tabu search, genetic algorithms, and simulated annealing. These methods provide high-level strategies for finding solutions efficiently.

5. Linear Programming

Linear programming is a cornerstone in the field of energy management, providing a structured mathematical approach to optimizing resource use, streamlining operations, and reducing environmental impact. In the dynamic landscape of transportation, where efficiency is key and sustainability is imperative, linear programming is becoming a key tool for navigating the complex interplay between energy consumption, operational efficiency, and environmental protection.

At its core, linear programming is a mathematical technique that seeks to optimize an objective function subject to a set of linear constraints. In the context of energy management, this technique is becoming a catalyst for optimizing fuel consumption, minimizing emissions, and improving energy efficiency in transportation systems. Linear programming models provide a systematic framework for decision making, helping to allocate resources while meeting operational constraints.

Linear programming plays a key role in determining the most efficient routes for vehicles, ships, or transportation networks. By taking into account variables such as distance, fuel consumption, and time constraints, it helps determine the optimal paths that minimize energy consumption and meet operational requirements.

The efficient use of resources such as fuel, time, and vehicle capacity is critical to transportation systems. Linear programming models help to optimally allocate these resources across fleets or routes, ensuring that energy consumption is minimized without compromising performance.

By optimizing schedules, minimizing downtime, and balancing load factors, linear programming helps improve vehicle efficiency. This makes it easier to make strategic decisions to reduce energy waste and increase overall productivity.

Linear programming algorithms provide near-optimal solutions to energy management problems, enabling accurate resource allocation and operational planning.

Рисунок В.3 – Сторінка 3

These models enable real-time decision making by providing information for route planning, resource allocation, and operational planning.

By optimizing fuel consumption and reducing emissions, linear programming makes a significant contribution to reducing the environmental impact of transportation systems.

While linear programming provides powerful tools for managing energy consumption, it is not without limitations. It assumes linear relationships between variables and constraints, which can oversimplify the complexity of real-world transportation systems. Future developments aim to address these limitations by integrating nonlinear models and advanced optimization techniques to accurately model more complex transportation dynamics.

Linear programming is a fundamental pillar in the quest for efficient and sustainable energy management in transportation systems. Its application to route optimization, resource allocation, and operations planning paves the way for reducing energy consumption, minimizing environmental impact, and increasing efficiency, ultimately leading transportation systems to a future where progress is seamlessly integrated with environmental responsibility.

6. Genetic algorithms

Genetic algorithms (GAs) represent an advanced approach to solving complex optimization problems, and their application to energy management in transportation systems heralds a transformative paradigm. Based on the principles of natural selection and evolutionary processes, GAs offer innovative solutions that optimize resource utilization, reduce energy consumption, and mitigate the environmental impact of various transportation modes.

GAs mimic the process of natural selection, using the principles of selection, reproduction, and mutation to iteratively evolve solutions to complex problems. In the area of energy management:

GAs excel at finding optimal routes for vehicles, taking into account factors such as fuel economy, traffic conditions, and time constraints. By developing and refining potential solutions, they identify routes that minimize energy consumption while meeting operational requirements.

These algorithms help optimize fleet performance by determining the best vehicle configuration, scheduling, and resource allocation to minimize energy loss across the fleet.

GAs play an important role in the development of energy-efficient vehicles, optimizing engine performance, aerodynamics, and vehicle weight to improve fuel efficiency and reduce overall energy consumption.

GAs explore large solution spaces and provide near-optimal solutions to complex problems of optimizing many variables in transportation systems. They adapt to changing environments and dynamic conditions, making them suitable for real-time decision making in transportation operations.

GAs contribute to innovative solutions by exploring unconventional paths and configurations that may be overlooked by human-designed algorithms. The computational requirements of GAs can be intensive, requiring significant computing resources. Tuning the parameters for optimal performance and convergence is challenging, but offers opportunities for improvement. Combining the algorithms with other optimization methods, such as neural networks or metaheuristic algorithms, increases their efficiency and effectiveness.

The evolution of GA continues, with promising advances aimed at addressing current limitations and further optimizing energy management in transportation systems. Future developments will focus on improving scalability, increasing convergence performance, and integrating GA with new technologies to achieve even greater efficiency and sustainability.

Genetic algorithms are emerging as a pioneering force in the revolution of energy management in transportation systems. Their application in route optimization, fleet management, and vehicle design heralds a future where transportation is not only efficient, but also environmentally sustainable. By mimicking the evolutionary processes of nature, GAs are leading us to a greener, more energy-efficient future of transportation, where innovation and nature-inspired algorithms work together to reduce environmental impact and increase operational efficiency.

7. Ant colony optimization

Ant Colony Optimization (ACO) is a powerful biological algorithm that mirrors the behavior of ants foraging for food. In the field of energy management in transportation systems, ACO is emerging as a transformative force, offering innovative solutions that optimize routes, reduce fuel consumption, and minimize environmental impact.

ACO algorithms model the behavior of ants as they communicate and navigate to find the shortest path to food sources. This approach uses pheromone trails and heuristic information to iteratively converge on optimal solutions.

ACO algorithms are ideal for finding the most energy-efficient routes for vehicles or ships. By mimicking the communication between ants using pheromones, these algorithms determine the paths that minimize fuel consumption, taking into account factors such as distance, traffic, and energy efficiency.

In urban transportation systems, ACO helps optimize traffic flow by identifying routes that minimize congestion, reduce idle time, and optimize traffic signals to improve fuel economy.

ACO helps optimize the allocation of resources across transportation networks by scheduling deliveries and vehicle routes to minimize energy consumption and optimize resource utilization.

Рисунок В.4 – Сторінка 4

ACO explores multiple paths and configurations, providing near-optimal solutions to complex transportation optimization problems. ACO adapts to dynamic and changing conditions, making it suitable for real-time decision making in transportation operations. By mimicking the self-organization and decentralized decision-making of ants, ACO promotes innovative solutions in energy management.

ACO can be a computationally intensive process that requires parameter optimization for efficiency. Fine-tuning of ACO parameters is critical for optimal convergence, opening opportunities for further research and improvement.

As technology advances, ACO algorithms are expected to continue to evolve. Future developments aim to reduce computational complexity, increase scalability, and integrate ACO with new technologies to improve transportation efficiency and sustainability.

Ant Colony Optimization is an innovative way to rethink energy management in transportation systems. Its application to route optimization, traffic flow management, and resource allocation heralds a future where transportation operations are not only efficient, but also environmentally conscious. Inspired by the principles of organization in nature, ACO algorithms pave the way for a sustainable, energy-efficient transportation ecosystem where biological algorithms guide us to reduce our environmental impact and optimize our energy consumption.

8. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a biological algorithm that models the social behavior of organisms, including the flocking and swarming patterns observed in birds and fish. In the field of energy management in transportation systems, PSO is emerging as a dynamic and effective tool that provides innovative solutions to optimize routes, increase fuel efficiency, and reduce environmental impact.

PSO algorithms are based on the collective behavior of organisms in a swarm. Individuals (particles) within the swarm cooperate and communicate by exchanging information and seeking optimal solutions through iterative movement in the solution space.

PSO is well suited for determining energy-efficient routes for vehicles, ships, or transportation networks. By simulating the movement of particles, these algorithms identify paths that minimize fuel consumption, taking into account factors such as distance, traffic, and energy efficiency.

By optimizing operations, PSO helps determine the best vehicle configuration, scheduling, and resource allocation to minimize fleet energy consumption.

PSO contributes to the development of energy-efficient vehicles by optimizing engine performance, aerodynamics, and vehicle weight, resulting in improved fuel efficiency and reduced energy consumption.

Benefits and Impacts.

PSO explores a wide variety of paths and configurations, providing near-optimal solutions to complex transportation optimization problems.

PSO adapts to changing environments and evolving conditions, making it suitable for real-time decision making in transportation operations.

By mimicking swarm behavior, PSO uses collective intelligence to find innovative solutions to manage energy consumption.

Optimization of PSO parameters is critical for convergence and efficiency. PSO can be a computationally intensive process that requires optimization for scalability and performance.

Integrating PSO with complementary optimization techniques can increase its effectiveness in complex transportation systems.

As technology advances, PSO algorithms are expected to continue to evolve. Future developments will address computational complexity, increase convergence, and integrate PSO with new technologies to improve transportation efficiency and sustainability.

Particle Swarm Optimization represents an advanced approach to revolutionize the management of energy consumption in transportation systems. Its application in route optimization, fleet management, and vehicle design provides a glimpse into a future where transportation is not only efficient, but also environmentally sustainable. By following the natural principles of cooperation, PSO algorithms pave the way for a more sustainable and energy efficient transportation ecosystem, where innovative algorithms guide us to reduce our environmental impact and optimize energy consumption.

9. Annealing simulation

Simulated Annealing (SA) is a powerful optimization method inspired by the physical process of annealing in metallurgy. It is a versatile algorithm used in a wide variety of fields, including energy management in transportation systems. SA provides a unique approach to solving complex optimization problems to minimize energy consumption, optimize routes, and reduce environmental impact.

The SA algorithm mimics the annealing process in metallurgy, where metals are heated and gradually cooled to reduce defects and produce a more stable structure. Similarly, SA gradually approaches optimal solutions, allowing for inferior decisions from time to time to avoid local optima.

SA can find energy-efficient routes for vehicles or ships. By exploring and gradually cooling the system, the algorithm identifies paths that minimize fuel consumption, taking into account factors such as distance, traffic conditions, and energy efficiency.

By optimizing vehicle scheduling, SA helps minimize downtime, improve utilization, and reduce energy costs during transportation operations.

Рисунок В.5 – Сторінка 5

SA helps optimize resource allocation across transportation networks, planning deliveries and vehicle routes to minimize energy consumption and increase overall efficiency.

Benefits and Impact

SA explores multiple solutions, allowing you to identify near-optimal paths and configurations in complex transportation optimization problems.

SA adapts to changing conditions, enabling real-time decision making in transportation operations.

SA's ability to make worse decisions from time to time helps avoid getting stuck on local optimal solutions, leading to better overall results.

Parameter Tuning: Optimizing SA parameters is essential for achieving optimal convergence performance and solution quality.

SA can be computationally intensive, requiring optimization for scalability and efficiency.

Integrating SA with complementary optimization techniques can increase its effectiveness in solving complex transportation optimization problems.

As technology advances, SA algorithms continue to evolve. Future advances will address computational complexity, increase convergence, and integrate SA with new technologies to improve transportation efficiency and sustainability.

Simulated Annealing is a sophisticated tool for rethinking energy management in transportation systems. Its application to route optimization, vehicle scheduling, and resource allocation promises a future where transportation operations are not only efficient, but also environmentally conscious. By mimicking the annealing process, SA algorithms lead us to reduce environmental impact and optimize energy consumption, paving the way for a more sustainable and efficient transportation ecosystem.

10. Dynamic Programming

Dynamic Programming (DP) is a powerful mathematical optimization technique used in a variety of fields, including energy management in transportation systems. Known for its ability to solve complex problems by breaking them down into simpler subproblems, DP offers innovative solutions to optimize routes, reduce fuel consumption, and improve overall transportation efficiency.

At its core, Dynamic Programming solves a complex problem by breaking it down into smaller subproblems, solving each subproblem only once, and storing the solution. This bottom-up approach allows you to obtain optimal solutions from the optimal solutions of its subproblems.

DP is ideal for finding energy-efficient routes for vehicles, ships, or transportation networks. By considering converging subproblems, it identifies paths that minimize fuel consumption, taking into account variables such as distance, traffic conditions, and energy efficiency.

By optimizing vehicle performance, DP helps reduce idle time, optimize utilization, and streamline work schedules to minimize energy consumption during transportation operations.

DP helps to efficiently allocate resources such as fuel and time across transportation networks, plan deliveries and vehicle routes to minimize energy consumption, and increase overall efficiency. Benefits and Impact

DP ensures that optimal subproblem solutions contribute to overall optimal solutions by providing efficient solutions to complex optimization problems.

DP preserves subproblem solutions, reducing redundant computations and increasing computational efficiency.

DP adapts to changing conditions, making it suitable for real-time decision making during transportation operations.

DP may face scalability and computational complexity issues for larger problems.

Balancing optimal solutions and computational efficiency requires careful consideration of tradeoffs.

The applicability of DP may be limited by computational resources and real-time constraints in dynamic transportation systems.

As technology advances, DP algorithms continue to evolve. Future developments are aimed at solving scalability problems, increasing computational efficiency, and integrating DP with new technologies to improve transportation efficiency and sustainability.

Dynamic programming is becoming the main tool for optimizing energy management in transportation systems. Its use in route optimization, resource allocation, and operations planning allows us to look to a future where transportation is not only efficient, but also environmentally conscious. By breaking down complex problems into manageable subproblems, DP algorithms guide us to reduce environmental impact and optimize energy consumption, creating a more sustainable and efficient transportation ecosystem.

11. Metaheuristic Algorithms

Metaheuristic algorithms represent a class of innovative and versatile optimization methods that go beyond traditional problem solving techniques. Designed to solve complex optimization problems, including energy management in transportation systems, these algorithms provide dynamic and adaptive solutions to minimize fuel consumption, optimize routes, and reduce environmental impact.

Metaheuristics are high-level strategies that guide the exploration of solution spaces to find near-optimal solutions without guaranteeing the absolute optimum. These algorithms are characterized by their flexibility, adaptability, and ability to efficiently traverse large solution spaces.

Metaheuristic algorithms are ideal for finding energy-efficient routes for vehicles, ships, or transportation networks. Using strategies such as exploration and exploitation, these algorithms determine paths that minimize fuel consumption by taking into account various factors such as distance, traffic conditions, and energy efficiency.

Рисунок В.6 – Сторінка 6

When optimizing fleet operations, metaheuristics help determine the optimal vehicle configuration, scheduling, and resource allocation to minimize fleet energy consumption.

Metaheuristic algorithms help design energy-efficient vehicles by optimizing engine performance, aerodynamics, and vehicle weight, resulting in improved fuel efficiency and reduced energy consumption.

Benefits and Impact.

Metaheuristics can solve a wide range of optimization problems, providing tailored solutions in dynamic transportation systems.

These algorithms efficiently explore large solution spaces, providing near-optimal solutions to complex optimization problems.

Metaheuristics facilitate real-time decision making, enabling rapid response to changing conditions in transportation operations.

Optimization of metaheuristic parameters is critical for achieving optimal convergence rates and solution quality.

Metaheuristics can be computationally intensive, requiring optimization for scalability and efficiency.

Combining multiple metaheuristics or integrating them with additional optimization techniques can increase their effectiveness.

As technology advances, metaheuristic algorithms continue to evolve. Future advances will address computational complexity, increase convergence, and integrate these algorithms with new technologies to improve transportation efficiency and sustainability.

Metaheuristic algorithms are innovative tools for transforming the management of energy consumption in transportation systems. Their application in route optimization, fleet management, and vehicle design allows us to look into a future where transportation becomes not only efficient, but also environmentally conscious. By using high-level strategies to explore decision spaces, metaheuristics guide us to reduce environmental impact and optimize energy consumption, contributing to a more sustainable and efficient transportation ecosystem.

12. Heuristic Algorithms

Known for their simplicity and efficiency, heuristic algorithms serve as indispensable tools for solving optimization problems, including energy management in transportation systems. These algorithms provide practical and intuitive solutions to minimize fuel consumption, optimize routes, and reduce environmental impact, making them a valuable asset in the quest for efficient and environmentally friendly transportation.

Heuristics are problem-solving approaches that aim to find near-optimal solutions in a reasonable amount of time. They emphasize speed and practicality over guarantees of finding the absolute best solution, making them well suited to complex and dynamic systems such as transportation.

Heuristic algorithms excel at finding good enough routes for vehicles, ships, or transportation networks. Using intuitive rules and strategies, these algorithms determine the paths that minimize fuel consumption, taking into account factors such as distance, traffic conditions, and energy efficiency.

When optimizing fleet operations, heuristics help determine efficient vehicle configurations and plan and allocate resources to minimize fleet energy consumption.

The heuristic facilitates the efficient allocation of resources such as fuel and time among transportation networks, delivery schedules, and vehicle routes to minimize energy consumption and increase overall efficiency.

Benefits and Impact.

Heuristics provide simple solutions that are easy to implement and interpret, making them valuable for real-world applications.

These algorithms are fast, providing practical solutions in a reasonable time frame for dynamic transportation systems.

Heuristics adapt to changing conditions and uncertainties, making them suitable for rapid decision making in transportation operations.

Heuristics cannot always guarantee the best solution, but focus on acceptable, near-optimal solutions.

Trade-offs: The balance between solution quality and computational efficiency requires careful consideration.

Combining different heuristic approaches or integrating them with other optimization methods can increase their effectiveness.

As technology advances, heuristic algorithms continue to evolve and find new applications. Future developments aim to eliminate limitations, improve the quality of solutions, and integrate heuristics with new technologies to improve transportation efficiency and sustainability.

Heuristic algorithms serve as pragmatic tools to revolutionize energy management in transportation systems. Using intuitive rules and practical strategies, heuristics guide us to reduce environmental impact and optimize energy consumption, laying the foundation for a more sustainable and efficient transportation environment.

13. Rationale for Research Methods

Scientific research is the systematic analysis of phenomena and processes, studying their influence of various factors and interactions in order to arrive at convincing and useful solutions for science and practice. Research methods include the use of induction and deduction, analysis, synthesis, and comparison of both theoretical and practical aspects.

In this case, the theory explores algorithms for optimizing energy consumption in transportation systems, including their characteristics, principles of operation, possible implementations, advantages and disadvantages to improve system efficiency.

Рисунок В.7 – Сторінка 7

There are several research methods, but in this case an empirical approach was chosen to compare different algorithms for optimizing energy consumption in transportation systems. This method is the most appropriate because it requires real measurements. It allows us to determine which algorithms work better in practice and to determine their relative effectiveness in research.

The methodology of this study is a combination of methods used to describe the research. The main method chosen was the logical method of cognition, which is used to solve problems analytically, explain events and phenomena, describe problems and identify ways to solve them in empirical and theoretical tasks.

14. Comparison methods for energy saving criterion

Linear programming:

The energy efficiency formula for linear programming can focus on reducing energy consumption relative to the baseline or initial energy consumption.

$$\text{Energy Efficiency} = \frac{\text{Initial Energy Consumption} - \text{Final Energy Consumption}}{\text{Initial Energy Consumption}} \times 100\%$$

Reduce environmental impact:

$$\text{Environmental Impact Reduction (LP)} = \text{Initial Impact (LP)} - \text{Final Impact (LP)}$$

Criteria: Operational performance

Execution Time: Evaluate the time it takes each algorithm to solve a given problem.

Record the time in milliseconds or seconds that the algorithms take to complete their tasks.

Solution Quality: Evaluate the quality or optimality of the solutions generated by each algorithm.

Define a quantitative quality metric specific to the problem domain (e.g., distance traveled, fuel consumption, etc.) or use objective metrics (minimization/maximization).

Composite metric: Create a composite metric that includes both lead time and solution quality.

Weight the metrics according to their relative importance.

$$\text{Operative Performance} = \frac{\text{w1} \times \text{Execution Time} + \text{w2} \times \text{Solution Quality}}{\text{w1} + \text{w2}}$$

where w1, w2 represent the weights assigned to execution time and solution quality, respectively.

Measure and record the execution time of each algorithm for different problem sizes or scenarios.

Evaluate the quality of the solutions produced by each algorithm based on predefined metrics.

Combine execution time and solution quality using a composite metric formula to obtain an overall operational performance score for each algorithm.

Compare the aggregate scores of all algorithms to determine which algorithms perform better in terms of operational performance. This comprehensive evaluation helps you select the most effective algorithm(s) based on time efficiency and solution quality.

Scalability and Adaptability.

Scalability: Measure how algorithm performance changes with increasing problem size.

Evaluate runtime or memory consumption as problem size or complexity increases.

Adaptability: Evaluate how well the algorithm handles changes or variations in the problem without significantly degrading performance.

Test the performance of the algorithm in different scenarios or problem variations.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Evaluate algorithm performance metrics (execution time, memory usage) for problems of varying size or complexity.

Track how these metrics change as the problem scales, indicating the scalability of each algorithm.

Test the adaptability of the algorithms by making variations or changes to the problem parameters and observing how well they handle these changes without significantly degrading performance.

Analyze and compare the scalability and adaptability of each algorithm based on observed changes in performance as the size or complexity of the problem increases or under different variations of the problem scenarios. This evaluation will help you determine which algorithms scale well and adapt effectively to different situations.

Real-time implementation

Binary evaluation: Determine if the algorithm can satisfy real-time constraints.

Assign a binary value: 1 if the algorithm can be implemented in real time, 0 if not.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Estimate the execution time of each algorithm under different scenarios or problem sizes.

Set a threshold or benchmark for real-time implementation (e.g., execution time less than a certain limit is considered real-time).

Рисунок В.8 – Сторінка 8

If an algorithm's execution time consistently meets the defined threshold across all scenarios, mark it as real-time (1) or not (0).

Compare the binary score of each algorithm to determine its suitability for real-time implementation. Algorithms with a "1" are suitable for real-time execution, while algorithms with a "0" may not meet real-time constraints. This comparison will help you identify algorithms that are suitable for real-time applications.

Computing requirements for real-time implementation.

Time complexity: Measure the time complexity of an algorithm, typically expressed in Big O notation, to understand how its execution time grows with the size of the input data.

Space complexity: Estimate the space requirements of an algorithm by specifying the memory or storage it consumes as the problem size increases.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Analyze the time complexity of each algorithm, determining its efficiency relative to the size of the input.

Estimate the space complexity by understanding the memory or storage requirements as the problem grows.

Express the time and space complexity for each algorithm using Big O notation or appropriate mathematical expressions.

Compare the time and space complexity of the algorithms to determine their computational requirements for real-time implementation. Algorithms with lower time and space complexity (e.g., lower Big O values) are generally more suitable for real-time implementation in transportation systems due to their efficient use of resources. This comparison will help to identify algorithms suitable for real-time implementation.

The cost-effectiveness evaluation of algorithms involves evaluating their cost-effectiveness in achieving the desired improvements. Here is an approach to comparing algorithms based on the cost-effectiveness criterion:

Criteria: Cost Effectiveness

Cost: Estimate the costs associated with implementing and running each algorithm. This may include initial setup costs, computing resources, and maintenance costs.

Improvement Achieved: Measure the improvements or benefits achieved by applying the algorithm, such as reduced energy consumption, optimized decisions, or minimized operational costs.

Cost Effectiveness: Calculate the cost-effectiveness ratio, which indicates the cost-effectiveness of the algorithm in achieving the improvements.

$$\text{Economic Efficiency} = \frac{\text{Cost}}{\text{Improvement achived}}$$

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Estimate the cost of implementing and maintaining each algorithm in a given scenario or problem domain.

Measure the improvements achieved by applying each algorithm by quantifying the benefits or optimizations gained.

Calculate the cost-effectiveness ratio using a formula for each algorithm, taking into account the ratio of costs incurred to improvements achieved.

Compare the cost-effectiveness ratios of the algorithms to determine which algorithms provide the best cost-effectiveness in terms of improvements. Algorithms with lower cost-effectiveness ratios, indicating greater improvements at lower cost, are considered more cost-effective. This comparison will help you select the algorithms that provide the best balance of cost and benefit.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Estimate the cost of implementing and maintaining each algorithm in a given scenario or problem domain.

Measure the improvements achieved by applying each algorithm by quantifying the benefits or optimizations gained.

Calculate the cost-effectiveness ratio for each algorithm using a formula that takes into account the ratio of costs incurred to improvements achieved.

Compare the cost-effectiveness ratios of the algorithms to determine which algorithms provide the best cost-effectiveness in terms of improvements. Algorithms with lower cost-effectiveness ratios, indicating greater improvements at lower cost, are considered more cost-effective. This comparison will help you select the algorithms that provide the best balance of cost and benefit.

Durability and reliability.

Robustness: Measures the ability of an algorithm to consistently produce correct and reliable results across different scenarios or data sets.

Stability: Evaluate the stability of an algorithm by checking how sensitive it is to changes in input data or parameters. A stable algorithm provides consistent performance despite variation.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Рисунок В.9 – Сторінка 9

Run multiple trials with different data sets or scenarios to evaluate the consistency of results produced by each algorithm.

Introduce variations or perturbations in the input parameters to evaluate the stability of the algorithms.

Quantify reliability and stability metrics for each algorithm based on observed behavior, error rates, or deviations from expected results.

Comparative analysis: Compare the reliability and stability scores of algorithms to determine which ones consistently produce reliable results across different scenarios or data sets and exhibit stable behavior in response to changes.

Algorithms with higher consistency, lower error rates, and less sensitivity to input variations are considered stronger and more reliable.

This comparison helps identify algorithms that consistently produce reliable results and are less prone to bias or error, highlighting their strength and reliability.

Regulatory compliance.

Evaluate the result: Evaluate the results or solutions generated by algorithms against regulatory standards or constraints. This may include ensuring that solutions meet certain legal or security requirements.

Industry Standards: Analyze the extent to which the algorithm's results are consistent with industry guidelines, regulations, or best practices. For example, in transportation systems, algorithms must comply with safety protocols or environmental regulations.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Examine the results or solutions produced by each algorithm in the context of the regulatory requirements applicable to the transportation system or related domain.

Verify that the solutions provided by the algorithms comply with established regulations, safety standards, or industry norms.

Quantify the level of compliance achieved by each algorithm based on the alignment of its results with regulatory requirements.

Benchmark: Compare the level of compliance demonstrated by each algorithm to determine which produce results that better meet regulatory requirements or industry standards.

Algorithms that produce solutions that are closer to the required regulations or standards are considered more compliant.

This comparison helps to assess the degree to which the results of each algorithm meet the required regulatory requirements or industry standards in the area of transportation systems.

Convenience and Integration.

Ease of implementation: Evaluate the ease and simplicity of implementing each algorithm into existing systems or frameworks.

Compatibility: Evaluate how well the algorithm integrates with different platforms, technologies, or software architectures without requiring significant modifications.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Analyze the implementation process for each algorithm, taking into account the ease of adaptation into existing systems. This may include assessing the complexity of code integration or program dependencies.

Evaluate the compatibility of the algorithms with different software architectures or platforms. Algorithms that can be easily integrated with minimal customization are more convenient.

Quantify the level of usability and integration for each algorithm based on implementation complexity and compatibility metrics.

Benchmark: Compare the usability and integration scores of algorithms to determine which offer smoother integration processes and better compatibility with existing systems.

Algorithms with higher usability and integration scores, indicating easier implementation and seamless integration, are considered more usable and compatible.

This comparison will help select algorithms that are easier to implement and integrate into transportation systems or related structures, reducing the complexity of adoption and ensuring smooth integration.

User Adaptability.

User interface and interaction:

Evaluate the accessibility and usability of interfaces or tools associated with the implementation of these algorithms.

User training and support: Evaluate the ease of learning and using the algorithms, including the availability of documentation, tutorials, or support materials.

Applications: Linear programming, genetic algorithms, ant colony optimization, particle swarm optimization, annealing simulation, dynamic programming, heuristic algorithms, metaheuristic algorithms:

Evaluate the interfaces or tools provided with each algorithm, considering their intuitiveness, simplicity, and ease of use.

Analyze the availability and quality of support materials (documentation, tutorials, etc.) to facilitate user understanding and implementation.

Quantify user adoption for each algorithm based on UI usability metrics and the availability of comprehensive support materials.

Рисунок В.10 – Сторінка 10

Comparative analysis: Compare the usability scores of algorithms to determine which algorithms offer more user-friendly interfaces and better support resources.

Algorithms with higher usability scores, indicating easier-to-use interfaces and comprehensive support materials, are considered more user-friendly.

This comparison will help select algorithms that provide users with interfaces and resources that are easy to understand, learn, and implement, thereby increasing overall user adaptability.

Conclusions

In the course of this task, the subject area was analyzed and algorithms for optimizing energy consumption in transportation systems were considered. The advantages and disadvantages of the algorithms were described and evaluation criteria were proposed.

As a result, a research report was prepared, which included the formulated measurable criteria for comparing the algorithms, described in detail and argued the use of each of them and when they could be neglected. The key metrics chosen to compare the technologies were

- Energy savings;

- Reduction of environmental impact;

- Operational efficiency;

- Scalability and adaptability;

- Real-time implementation;

- computational requirements of the algorithm for real-time implementation in transportation systems;

- Economic efficiency;

- Durability and reliability;

- Regulatory compliance;

- Ease of use and integration;

- User adaptability;

In the current study, we proposed relevant ways to measure each of the presented metrics, formulated criteria, and mathematical formulas used to calculate the numerical values of these metrics.

Conflict of Interest

The authors declare no conflict of interest.

References

[1] U.S. Bureau of Transportation Statistics. 2018. Available online: https://www.bts.gov/transportation-economic-trends/tet-2018-chapter-2-contributioneconomy (accessed on 15.12.2023).

[2] European Union. Statistical Pocketbook 2017: EU Transport in Figures; Publications Office of the European Union: Brussels, Belgium, 2017; ISBN 978-992-79-62311-0.

[3] Chen, G.; Wu, X.; Guo, J.; Meng, J.; Li, C. Global overview for energy use of the world economy: Household-consumption-based accounting based on the world input-output database (WIOD). Energy Econ. 2019, 81, 835–847.

[4] United Nations Department of Economics and Social Affairs. 2019. Available online: https://population.un.org/wpp/Download/Standard/Population/ (accessed on 15.12.2023).

[5] Bektaş, T.; Ehmke, J.F.; Psaraftis, H.N.; Puchinger, J. The role of operational research in green freight transportation. Eur. J. Oper. Res. 2019, 274, 807–823.

[6] Juan, A.; Mendez, C.; Faulin, J.; De Armas, J.; Grasman, S. Electric vehicles in logistics and transportation: A survey on emerging environmental, strategic, and operational challenges. Energies 2016, 9, 86.

[7] Fan, Y.V.; Klemeš, J.J.; Walmsley, T.G.; Perry, S. Minimising energy consumption and environmental burden of freight transport using a novel graphical decision-making tool. Renew. Sustain. Energy Rev. 2019, 114, 109335.

[8] Dekker, R.; Bloemhof, J.; Mallidis, I. Operations Research for green logistics–An overview of aspects, issues, contributions and challenges. Eur. J. Oper. Res. 2012, 219, 671–679.

[9] Faulin, J.; Grasman, S.E.; Juan, A.A.; Hirsch, P. Sustainable Transportation: Concepts and Current Practices. In Sustainable Transportation and Smart Logistics; Elsevier: Amsterdam, The Netherlands, 2019; pp. 3–23.

[10] Neumann, F.; Witt, C. Combinatorial optimization and computational complexity. In Bioinspired Computation in Combinatorial Optimization; Springer: Berlin, Germany, 2010; pp. 9–19.

[11] Glover, F.W.; Kochenberger, G.A. Handbook of Metaheuristics; Springer Science & Business Media: Berlin, Germany, 2006; Volume 57.

[12] Psaraftis, H.N.; Kontovas, C.A. Speed models for energy-efficient maritime transportation: A taxonomy and survey. Transp. Res. Part C Emerg. Technol. 2013, 26, 331–351.

[13] Ríos-Mercado, R.Z.; Borraz-Sánchez, C. Optimization problems in natural gas transportation systems: A state-of-the-art review. Appl. Energy 2015, 147, 536–555.

[14] Yang, X.; Li, X.; Ning, B.; Tang, T. A survey on energy-efficient train operation for urban rail transit. IEEE Trans. Intell. Transp. Syst. 2015, 17, 2–13.

[15] Tranfield, D.; Denyer, D.; Smart, P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br. J. Manag. 2003, 14, 207–222.

Рисунок В.11 – Сторінка 11

ДОДАТОК Г

Експертний висновок результатів перевірки кваліфікаційної роботи на відповідність оформлення вимогам ДСТУ 3008: 2015