MINISTRY OF EDUCATION AND SCIENCE OF UKRAINE

NATIONAL AVIATION UNIVERSITY

Faculty of aeronautics, electronics and telecommunications

Department of aviation computer-integrated complexes

ADMIT TO DEFENSE

Head of the graduation department

________ Victor SINEGLAZOV

"___"_______________2024 y.

QUALIFICATION WORK

(EXPLANATORY NOTE)

GRADUATE DEGREE OF EDUCATION

"BACHELOR"

Specialty 151 "Automation and computer-integrated technologies"

Educational and professional program "Computer-integrated technological processes and production"

Topic: Improving Mesh Network Efficiency for UAV Control Using Machine Learning

Performer: student of group IK-323/stn Smishchuk Bogdan Mykolayovych

Leader: Senior teacher Dolgorukov Serhii Olegovich

Norm controller: _________ Filyashkin M.K.
(signature)

Kyiv – 2024

МІНІСТЕРСТВО ОСВІТИ І НАУКИ УКРАЇНИ

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ

Факультет аеронавігації, електроніки та телекомунікацій

Кафедра авіаційних комп'ютерно-інтегрованих комплексів

ДОПУСТИТИ ДО ЗАХИСТУ

Завідувач випускової кафедри

________ Віктор СИНЄГЛАЗОВ

"___"_______________2024р.

КВАЛІФІКАЦІЙНА РОБОТА (ПОЯСНЮВАЛЬНА ЗАПИСКА)

ВИПУСКНИКА ОСВІТНЬОГО СТУПЕНЯ

"БАКАЛАВР"

Спеціальність 151 «Автоматизація та компю'терно-інтегровані технології»

Освітньо-професійна програма «Комп'ютерно-інтегровані технологічні процеси і виробництва»

Тема: Підвищення ефективності мережі Mesh для керування БПЛА із застосуванням машинного навчання

Виконавець: студент групи ІК-323/стн Сміщук Богдан Миколайович

Керівник: Старший викладач Долгоруков Сергій Олегович

Нормоконтролер: _ _________ Філяшкін М.К
(підпис)

Київ – 2024

MINISTRY OF EDUCATION AND SCIENCE OF UKRAINE

NATIONAL AVIATION UNIVERSITY

Faculty of Aeronautics, Electronics and Telecommunications

Department of aviation computer-integrated complexes

Educational degree: bachelor, Specialty 151 "Automation and computer-integrated technologies"

Educational and professional program "Computer-integrated technological processes and production"

APPROVED

Head of Department

________ Viktor SINEGLAZOV

“ ____ ” __________2024 y.

ASSIGNMENT

to perform the student's qualifying work

Smishchuk Bogdan Mykolayovych

1. The topic of the work: "Improving the efficiency of the Mesh network for UAV control using machine learning"

2. The term of the work: from 08.04.2024 to 16.06.2024

3. Initial data for the work: The development of the Mesh network optimization system using deep learning methods should be carried out for the average unmanned aerial vehicle of the "DJI Matrice 300 RTK" type.

4. Contents of the explanatory note (list of issues to be developed): 1. Analysis of modern use of unmanned aerial vehicles (UAVs); 2. Overview of universal UAVs that can be used with the Mesh system; 3. Comparison of different types of UAVs for use in the Mesh system; 4. Choosing a deep learning method for Mesh network optimization; 5. Development of the architecture of the proposed system; 6. Mathematical description of the deep learning method; 7. Algorithm of system operation with an example of Python code and necessary frameworks; 8. Selection of software and hardware for implementation (description of frameworks and tools); 9. Tasks of the deep learning method (listing the elements); 10. Determination of the criteria for the effectiveness of the deep learning method; 11. Application hardware and software. Analysis of advantages and disadvantages of the chosen method; 12 Comparison of the effectiveness of the selected method (table/graph); 13. Analysis of the obtained results and conclusions;

5. List of mandatory graphic material: 1. Structural diagrams of universal UAVs that can be used with the Mesh system. 2. Block diagram of the architecture of the proposed system. 3. Graph of efficiency of Mesh network management methods. 4. Table of comparison of efficiency of various types of UAVs for use in the Mesh system. 5. Scheme of interaction of system components (data collection module, data preprocessing module, deep learning module, decision making module, decision implementation module, user interface). 6. Control laws and structural diagram of the deep learning method for Mesh network optimization. 7. Chart of calculation results and comparison of the effectiveness of the selected method. 8. Charts or graphs demonstrating system performance (throughput, latency, reliability, cost, complexity of implementation). 9. Scheme of connecting hardware to the Mesh system. 10. Software scheme with Python code examples.

6**. Calendar plan-schedule**:

No	Task	Deadline	Performance note
1.	Analysis of literary sources	08.04.2024	
2.	Collection of information	09.04.2024	
3.	Overview of versatile UAVs that can be used with the Mesh system	10.04.2024-11.04.2024	
4.	Comparison of these UAVs	12.04.2024-13.04.2024	
5.	Choosing a machine learning method for Mesh network optimization	14.04.2024-15.04.2024	
6.	Development of the architecture of the proposed system (block diagram)	16.04.2024	
7.	Mathematical description of the deep learning method	17.04.2024-19.04.2024	
8.	Development of the algorithm of system operation with an example code in Python and the necessary frameworks	20.04.2024-23.04.2024	
9.	Selection of software and hardware tools for implementation (description of frameworks and tools)	24.04.2024-28.04.2024	
10.	Performance analysis and results	29.04.2024	
11.	Issuance of an explanatory note	30.04.2024	
12.	Issuance of an explanatory note	01.05.2024-09.06.2024	
13.	Creating a presentation	10.06.2024	

7. Issue date of the assignment____

Head: ____________________________________ Dolgorukov S.O

The task was accepted by __________________ Smishchuk B.M.

____ ” _______2024 y.

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ
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Кафедра авіаційних комп’ютерно-інтегрованих комплексів

Освітній ступінь: бакалавр Спеціальність 151 «Автоматизація та комп'ютерно-інтегровані технології»

Освітньо-професійна програма «Комп’ютерно-інтегровані технологічні процеси і виробництва»

ЗАТВЕРДЖУЮ
Завідувач кафедри
_________ Віктор СИНЄГЛАЗОВ
“ ___ ” _________2024 р.

ЗАВДАННЯ

на виконання кваліфікаційної роботи студента

Сміщука Богдана Миколайовича

1. Тема роботи: «Підвищення ефективності мережі Mesh для керування БПЛА із застосуванням машинного навчання»

2. Термін виконання роботи: з 08.04.2024 р. до 16.06.2024 р.

3. Вихідні дані до роботи: Розробку системи оптимізації мережі Mesh з використанням методів глибокого навчання проводити для середнього безпілотного літального апарата типу "DJI Matrice 300 RTK"**.**

4. Зміст пояснювальної записки (перелік питань, що підлягають розробці): 1.Аналіз сучасного використання безпілотних літальних апаратів(БПЛА); 2.Огляд універсальних БПЛА, які можуть використовуватись з системою Mesh; 3.Порівняння різних типів БПЛА для використання в системі Mesh; 4.Вибір методу глибокого навчання для оптимізації мережі Mesh; 5.Розробка архітектури пропонованої системи; 6.Математичний опис методу глибокого навчання; 7.Алгоритм роботи системи з прикладом коду на Python та необхідними фреймворками; 8.Вибір програмних та апаратних засобів для реалізації (опис фреймворків та інструментів); 9.Завдання методу глибокого навчання (розписання елементів); 10.Визначення критеріїв ефективності методу глибокого навчання; 11.Програмно-апаратний засіб застосування. Аналіз переваг та недоліків вибраного методу; 12Порівняння ефективності вибраного методу (таблиця/графік); 13.Аналіз отриманих результатів та висновки;

5. Перелік обов’язкового графічного матеріалу: 1.Структурні схеми універсальних БПЛА, які можуть використовуватись з системою Mesh. 2.Блок-схема архітектури пропонованої системи. 3.Графік ефективності методів управління мережами Mesh.4.Таблиця порівняння ефективності різних типів БПЛА для використання в системі Mesh. 5.Схема взаємодії компонентів системи (модуль збору даних, модуль попередньої обробки даних, модуль глибокого навчання, модуль прийняття рішень, модуль реалізації рішень, інтерфейс користувача). 6.Закони управління та структурна схема методу глибокого навчання для оптимізації мережі Mesh. 7.Графік результатів обчислень та порівняння ефективності вибраного методу. 8.Діаграми або графіки, що демонструють результати роботи системи (пропускна здатність, затримки, надійність, вартість, складність впровадження). 9.Схема підключення апаратних засобів до системи Mesh. 10.Схема програмного забезпечення з прикладами коду на Python.

6**. Календарний план-графік:**

№ п/п	Завдання	Термін виконання	Відмітка про виконання
1.	Аналіз літературних джерел	08.04.2023	
2.	Збір інформації	09.04.2024	
3.	Огляд універсальних БПЛА, які можуть використовуватись з системою Mesh	10.04.2024-11.04.2024	
4.	Порівняння цих БПЛА	12.04.2024-13.04.2024	
5.	Вибір методу машинного навчання для оптимізації мережі Mesh	14.04.2024-15.04.2024	
6.	**Розробка архітектури пропонованої системи (блок-схема)**	16.04.2024	
7.	**Математичний опис методу глибокого навчання**	17.04.2024-19.04.2024	
8.	**Розробка алгоритму роботи системи з прикладом коду на Python та необхідними фреймворками**	20.04.2024-23.04.2024	
9.	**Вибір програмних та апаратних засобів для реалізації (опис фреймворків та інструментів)**	24.04.2024-28.04.2024	
10.	**Аналіз ефективності та результати**	29.04.2024	
11.	Оформлення пояснювальної записки	30.04.2024	
12.	**Оформлення пояснювальної записки**	01.05.2024-09.06.2024	
13.	**Створення презентації**	10.06.2024	

7. Дата видачі завдання____

Керівник: ___________________________________ Долгоруков С.О

Завдання прийняв до виконання ________________ Сміщук Б.М.

____ ” _______2024 р.

Abstract

Thesis Explanatory Note "Improving Mesh Network Performance for UAV Control Using Machine Learning" contains 46 pages, 6 figures, 2 tables, 1 Python code 20 sources used.

Object of study- The object of the research is the Mesh network and its application for controlling unmanned aerial vehicles (UAVs).

Subject of study -The subject of the research is the theoretical foundations of Mesh networks, machine learning methods for optimizing their work, development of methods for increasing the efficiency of Mesh networks using machine learning, as well as experimental verification and analysis of results.

The goal of the work -The purpose of the work is to research the possibilities of using Mesh networks to control unmanned aerial vehicles, develop and optimize machine learning methods to optimize their work, develop a methodology for increasing the efficiency of the Mesh network using machine learning, as well as experimental verification of these methods and analysis of the obtained results.

Research methods -Research is carried out using analytical and experimental methods. Analysis of scientific literature, modeling of machine learning methods, development and implementation of software algorithms, experimental tests and analysis of the obtained data are used.

CONTENT

LIST OF CONVENTIONAL ABBREVIATIONS

UAV, UAV - unmanned aerial vehicle.

ML - machine learning

CSMA/CA - multiple access with channel separation and collision avoidance

UI - user interface

API - application programming interface

ML - machine learning

GPU - graphics processor

CPU - central processing unit

NN - neural network

CNN - convolutional neural network

RNN - recurrent neural network

Introduction

In recent years, unmanned aerial vehicles (UAVs) have become an integral part of many industries, including agriculture, environmental monitoring, rescue operations, logistics, and military operations. Their ability to perform complex tasks in conditions where human presence may be dangerous or impossible significantly increases the efficiency and safety of operations. However, a reliable communication system capable of adapting to changing environmental conditions is needed to coordinate many UAVs and ensure their smooth operation.

Mesh networks are a promising technology for creating such communication systems, as they are characterized by a decentralized structure and the ability to self-organize. These networks are resistant to the failure of individual nodes and provide uninterrupted communication even in difficult conditions. However, to get the most out of mesh networks, the network protocols that control routing and data transmission must be optimized.

The application of machine learning (ML) techniques offers the potential to optimize network protocols in cellular networks. The application of machine learning algorithms allows analyzing a significant amount of data about the state of the network and its environment in real time. This data is used to automatically adjust network parameters for optimal performance. This leads to improvements in key performance metrics such as latency, throughput and power consumption, which are vital for effective UAV control.

The relevance of this topic is due to the need to develop modern technologies that will ensure high reliability and efficiency of UAV control systems. As the popularity and importance of UAVs in various industries continues to grow, optimization of network protocols using machine learning is becoming a critical task. This research project is aimed at solving current problems related to increasing the efficiency of cellular networks, which will improve the coordination and performance of unmanned aerial vehicles.

The use of unmanned aerial vehicles in different areas requires the use of different communication and control methodologies. For example, in the agricultural sector, UAVs are used to monitor crops, spray plants and harvest crops. This requires coordination and rapid exchange of information between devices. In the context of rescue operations, the possibility of fast and reliable communication is of paramount importance to save lives. In military operations, the reliability of communication between UAVs is of primary importance for the successful execution of missions.

Therefore, research on improving the efficiency of mesh networks for controlling UAVs using machine learning is timely and important, as it meets the modern challenges and needs of the development of unmanned systems. Optimizing communication systems using the latest technologies will significantly increase the efficiency and reliability of UAVs, which will contribute to their wider use and increase the overall level of safety and productivity.

Chapter 1

Theoretical foundations of Mesh networks and their application for UAV control

1.1. Definition and classification of Mesh networks

Mesh networks are one of the most promising and powerful types of networks in the modern world of communications. Mesh networks are based on the principle of interconnectedness of the nodes that make up the network, and use wireless data transmission technologies to communicate with each other. A distinctive feature of mesh networks is their ability to work independently, without the need for centralized management. This property makes them well suited for scenarios where access to a central node is limited or unavailable.

Topologically, cellular networks can have a wide range of configurations. A fully cellular network is defined as a network in which every node is directly connected to every other node. This configuration provides a high level of spaciousness and reliability. In contrast, partially cellular networks can only have a limited number of direct connections between certain nodes, which can simplify the network structure and reduce implementation costs.

The main task of cellular networks is to facilitate data transmission between nodes. A variety of routing algorithms are used for this, including shortest path routing and adaptive routing. The choice of a particular routing algorithm depends on many variables, including the complexity of the network, the desired performance, and the need for reliability.

In addition, cellular networks may use different channel access control mechanisms to facilitate data transmission. The two most common channel access control protocols used in wireless networks are CSMA/CA (Channel Separation Multiple Access and Collision Avoidance) and TDMA (Channel Time Division Multiple Access). These protocols facilitate efficient data transmission in wireless networks.

1.2. Architectural features and operating principles of Mesh networks

The architecture of mesh networks is based on the principles of decentralization and self-organization, which makes them effective in many use cases. The main characteristics of the architectural and operational principles include:

1. Decentralization: Mesh networks have no central controller or node. Each node in the network can interact with other nodes, which avoids single-point-of-failure (one node, the failure of which can lead to the failure of the entire network) and ensures high network resilience.
2. Self-Organizing: Mesh networks can self-organize by discovering new nodes and establishing routes between them. This allows the network to adapt to changes in topology or node failures without the need for external guidance.
3. Multipath Routing: Nodes in a Mesh network can use multiple alternative routes for data transmission, which increases the resilience and reliability of the network. If one route fails, data can be rerouted through another route.
4. Flexibility and scalability: Mesh networks are easily scalable, allowing new nodes to be added or the network to expand without major changes to its architecture. This makes them effective in a variety of large-scale applications, from home networks to large urban infrastructure networks.
5. Routing Protocols: Specialized routing protocols such as AODV (Ad hoc On-Demand Distance Vector), OLSR (Optimized Link State Routing), and DSR (Dynamic Source Routing) are used to determine optimal paths for data transmission in Mesh networks. These protocols allow nodes to independently determine routes depending on network conditions.
6. Environment access protocols: To coordinate the access of nodes to a common communication environment in Mesh networks, various protocols are used, such as CSMA/CA (Carrier Sense Multiple Access with Collision Avoidance) or TDMA (Time Division Multiple Access), which ensure efficient use of the radio frequency spectrum and prevent collisions.

1.3. Application of Mesh networks for UAV control

Using mesh networks to control unmanned aerial vehicles (UAVs) opens up many potential ways to improve the efficiency and reliability of these systems. Mesh networks provide stable communication between the UAV and the ground station even in difficult conditions, allowing operators to maintain control over the devices at any time and in any environment.

In addition, they can be used to coordinate the actions of separate UAVs in difficult terrain or in the context of tasks that require the synchronization of several devices.

In addition, mesh networks allow you to build umbrella networks that provide coverage and communication over large areas.

These networks can be implemented with the support of systems of autonomous operation and redundancy, which ensures continuous operation and network communication in case of failure of some nodes.

In addition, mesh networks can be deployed in various locations, including in hard-to-reach or remote areas where standard means of communication may be unavailable or ineffective.

This makes them particularly useful for military operations, search and rescue operations, as well as for monitoring and surveillance of remote objects or territories.

It is also important to note that mesh networks can be easily expanded and modernized, which allows introducing new technologies and functions with minimal changes to existing systems.

This flexibility allows these networks to be adapted to different usage scenarios, ensuring their future sustainability and efficiency.

1.4. Main problems and challenges in the implementation of Mesh networks for UAVs

Although mesh networks have the potential to be an effective means of controlling unmanned aerial vehicles (UAVs), their implementation is accompanied by a number of problems and challenges. The main difficulties that arise include the following:

1. The field of network resource management is related to the efficient and rational use of network resources. Effective management of resources, such as link bandwidth and node energy, is of paramount importance in the context of cellular network architecture. This is due to the fact that it provides fault tolerance and network performance in conditions where resources are limited.
2. Routing management is an important aspect of network resource management. In the conditions of operation of Mesh networks on difficult terrain or with a large number of nodes, it is extremely important to ensure optimal route selection and avoid overloading of some nodes.
3. Immunity to interference and failures: Mesh networks must be able to withstand many potential sources of interference, including electromagnetic, terrain-related, and random node failures. Ensuring the stability and reliability of the network in conditions of failures is a significant challenge.
4. Data security is a key aspect of any network, especially in the context of mesh networks, which are vulnerable to various forms of attacks. It is extremely important to ensure the confidentiality, integrity and availability of data transmitted in the mesh network in order to protect it from cyber attacks and unauthorized access to information.
5. Scalability and extensibility are critical factors when designing a mesh network. When designing a mesh network, it is extremely important to consider its scalability and the ease with which it can be expanded to meet the growing needs and demands of users.

6. Energy efficiency is a crucial aspect to consider when designing a Mesh network. It is very important to ensure energy-efficient operation of Mesh-nodes in order to extend their service life and ensure their mobility in conditions of limited power sources.

Conclusion to the first chapter

Description of the theoretical foundations of Mesh networks and their application to the control of unmanned aerial vehicles (UAVs). Studying the definitions, classifications and architectural features of Mesh networks allowed us to understand their potential effectiveness in providing communication between UAVs and ground stations. In addition, the main problems and challenges in the implementation of Mesh networks for UAVs are identified, which poses a task for further research and development in this area.

Section 2

Overview of universal UAVs and machine learning methods

This chapter provides a detailed analysis of universal UAVs and machine learning techniques used to optimize network protocols. We will look at the different types of versatile UAVs, their features, advantages and disadvantages, and how they can be integrated into Mesh networks. Next, a comparison of these UAVs will be made, and machine learning techniques that can be applied to improve the efficiency of Mesh networks will also be considered.

2.1. Types of universal UAVs

Unmanned aerial vehicles (UAVs) can be classified according to various parameters such as design, engine type, flight range and others. Among the most common types of universal UAVs that can be used with the Mesh system are distinguished:

1. Quadcopters:

Fig. 1.1 Quadcopters.

- Ease of management, high maneuverability.
- Application: aerial photography, survey of territories.

2. Hexacopters:

Fig. 1.2 Hexacopters.

- Greater load capacity and reliability.
- Application: professional video shooting, cargo transportation.

3. Octocopters:

Fig. 1.3 Octocopters.

- Maximum stability, high load capacity.
- Application: work in strong wind conditions.

4. Fixed wing:

Fig. 1.4 Fixed wing

- Long duration of flight, high speed.
- Application: reconnaissance of large areas, delivery of goods.

5. Hybrid UAVs:

Fig. 1.5 Fixed wing

- Combining the advantages of multi-rotor and fixed-wing systems.
- Applications: tasks requiring vertical take-off and landing and fast horizontal flight.

2.2. Universal UAVs that can be used with the Mesh system

Unmanned aerial vehicles, also known as drones, are used in many fields such as agriculture, transportation, intelligence and military operations. Depending on mission requirements, there are different types of UAVs that can be effectively integrated with a mesh network to improve communication and coordination.

Integration with the Mesh system:

Versatile UAVs can be integrated with a Mesh system to improve communication and coordination between them. The Mesh system provides the following advantages:

- Communication stability: Due to the self-healing nature of Mesh, even if one or more nodes (drones) fail, the network will continue to function.
- Adaptability: The network automatically adjusts to the location and number of drones, ensuring optimal coverage and bandwidth.
- Scalability: The system is easily scalable, allowing new drones to be added without significant changes to the network configuration.

2.3. Comparison of universal UAVs

The comparison of versatile UAVs includes an analysis of their technical characteristics, such as flight range, payload capacity, flight duration, stability, as well as the ability to integrate with the Mesh network. Main parameters to be compared:

Flight Range: Determines the maximum distance the drone can fly from the starting point.

- Payload: The maximum payload mass that the drone can carry.
- Flight Duration: The amount of time the drone can stay in the air without recharging.
- Stability: The drone's ability to withstand adverse weather conditions and maintain stability in flight.
- Mesh Integration: How easily a drone can be integrated into a Mesh network and its ability to communicate with other network nodes.

Table 2.1 compares the different types of versatile unmanned aerial vehicles (UAVs) that can be used with the Mesh system, based on the main technical characteristics.

Table 2.1

Type of UAV	Flight range	Carrying capacity	Flight duration	Stability	Integration with Mesh
Quadcopter	High	average	average	High	Lung
Hexacopter	High	High	average	High	Lung
Fixed wing	High	High	Very high	average	Complicated
Hybrid	High	High	High	High	average

Based on the comparison of the presented types of UAVs, it can be determined that quadcopters and hexacopters can be more attractive options for use in the Mesh system. These types of UAVs have a long flight range, sufficient load capacity and stability in flight. In addition, they are easily integrated with the Mesh network, which simplifies their use for various mission tasks. However, the choice of a specific type of UAV also depends on the specifics of the mission itself and operating conditions.

2.4. Basic concepts and methods of machine learning

Machine learning is a subfield of artificial intelligence that uses algorithms and models trained on available data to perform specific tasks without the need for explicit programming. In the context of optimization of network protocols in mesh networks, machine learning becomes an indispensable tool for solving various tasks.

Basic concepts and methods of machine learning include:

Supervised learning is a machine learning method that uses a training dataset in which each example has a known output (label). This method is based on the assumption that there is a training data set in which each example is accompanied by a known result (label). The algorithm learns from this data and tries to determine the relationship between input and output. In the context of cellular networks, this approach can be used to predict traffic or classify data types.

Unsupervised learning is a method that does not require the use of labeled data. This method is used to detect hidden structures in an unlabeled data set. Algorithms are able to independently study the data structure and try to identify relationships and groups. In cellular networks, this can be used to cluster nodes according to their activity level or functional purpose.

The process of model fitting is as follows: It is the process of adjusting model parameters to match the characteristics of a given data set. This is an important step in many machine learning methodologies because it affects the accuracy and efficiency of the model.

The final stage of the process is model validation and evaluation. This step involves validating the model on a test data set to determine its performance, determine its accuracy, and assess its reliability.

2.5. Application of machine learning to optimize network protocols

The application of machine learning methods to optimize network protocols in Mesh networks opens wide prospects for improving their efficiency and productivity.

One of the key application areas of machine learning is analyzing network traffic and predicting the amount of data being sent between nodes.

Machine learning methods allow you to automatically adapt the allocation of resources and manage channel bandwidth depending on the current conditions of the network, which helps to maintain its stability and efficiency.

In addition, machine learning algorithms can detect anomalies in network behavior that may indicate attacks or malfunctions, thereby providing a high level of cybersecurity.

In addition, the application of machine learning allows you to optimize the operation of routing protocols in real time, choosing the most efficient routes taking into account current network conditions and user requirements.

Thus, the application of machine learning methods in Mesh networks opens up new opportunities for improving their efficiency, reliability and security, contributing to the further development of this type of networks.

2.6. Comparison of the efficiency of different machine learning methods for UAV Mesh networks

Comparing the performance of different machine learning methods is a key aspect in determining optimal optimization strategies for Mesh networks. Researchers analyze different approaches using different methods to find out which ones best meet the network's requirements.

Methods used:

1. **Neural networks**: This approach uses different neural network architectures for traffic analysis and routing optimization.
2. **Decision trees and random forests**: They are used for classification and prediction in Mesh networks.
3. **Support vector method (SVM)**: Used for classification and regression in Mesh networks.
4. **Clustering**: Used to group similar nodes or network areas.
5. **Deep learning**: This approach is used for complex network data analysis and decision-making tasks.

Comparison results:

1. **Effectiveness of traffic prediction**: Neural networks and deep learning have shown high accuracy in predicting traffic volumes.
2. **Performance and execution time**: Decision trees and random forests can be less computationally expensive.
3. **Immunity to noise and training data**: Some methods may be more robust to noise in the data and may perform better with insufficient training data.

Conclusion to the second chapter

This chapter provided an overview of universal UAVs and machine learning techniques that can be used to optimize network protocols. Examining the different types of UAVs and their capabilities has given us an idea of what systems can be integrated with Mesh networks. A review of machine learning techniques has shown their potential effectiveness in improving network performance and optimizing protocols.

Section 3

Development of a technique for increasing the efficiency of the Mesh network using machine learning

The goal is to develop deep learning models that can accurately predict the volume and type of network traffic at different points in time. This will allow the network to proactively respond to changes in load, thereby ensuring stable and high-performance operation. Accurate forecasts will help avoid congestion and optimal allocation of resources.

3.1. Choosing a machine learning method for Mesh network optimization

A deep learning method was chosen to optimize the Mesh network. This is due to a number of advantages that ensure high efficiency and accuracy in solving complex network optimization problems.

Deep learning is a subfield of machine learning that uses multilayer neural networks to automatically extract features and model complex nonlinear relationships in data. This approach has significant potential for use in Mesh networks, particularly in the areas of traffic prediction, traffic type classification, anomaly detection, and routing optimization.

The advantages of deep learning for mesh networks include high accuracy and automatic feature extraction.

Deep neural networks are capable of automatically extracting relevant features from the data, thus ensuring high accuracy of the created models. This is particularly useful in the context of cellular networks, where the data may be too diverse and complex for traditional methods. Processing large amounts of data is facilitated by deep learning.

Deep learning is particularly well-suited to processing large amounts of data, which is common in today's cellular networks. Deep learning models can be trained on large datasets to provide accurate predictions and optimization.

Ability to self-study:

Deep learning models can improve their performance over time through the process of learning on new data. This allows them to adapt to changes in network conditions and traffic dynamics.

Spatial and temporal data processing is a key aspect of deep learning.

Convolutional Neural Networks (CNNs) are particularly well suited for analyzing spatial data such as network topology. Recurrent neural networks (RNNs), including long-short-term memory (LSTM) and gated recurrent unit (GRU) variants, are well suited for analyzing time series data such as network traffic dynamics.

Application of deep learning in Mesh networks

1. **Traffic forecasting**:
    - Using deep neural networks to predict traffic volumes based on historical data. This helps to optimize the allocation of network resources and improve the quality of service.
2. **Classification of traffic types**:
    - Application of convolutional and recurrent neural networks for classification of different types of traffic. This allows you to prioritize important traffic and ensure effective network management.
3. **Detection of anomalies**:
    - Using deep learning techniques to detect anomalies in traffic that may signal outages or potential network attacks. This helps improve network security.
4. **Optimization of routing**:
    - Application of deep learning models for dynamic optimization of data routing in Mesh network. This ensures more efficient use of network resources and increases the reliability of data transmission.

Conclusion:

Deep learning is a powerful tool for optimizing mesh networks due to its ability to process large amounts of data, automatically extract important features, and adapt to changes in network conditions. The use of convolutional and recurrent neural networks allows for effective traffic prediction, classification, anomaly detection, and routing optimization, which overall improves the efficiency and reliability of the Mesh network.

3.2. Architecture of the proposed system

In order to achieve the goal of increasing the efficiency of the Mesh network with the help of deep learning, it is necessary to develop a complex system architecture that unites all components that ensure effective operation and interaction between them.

The system architecture consists of several key elements:

General structure of the system

The architecture of the proposed system consists of the following main components:

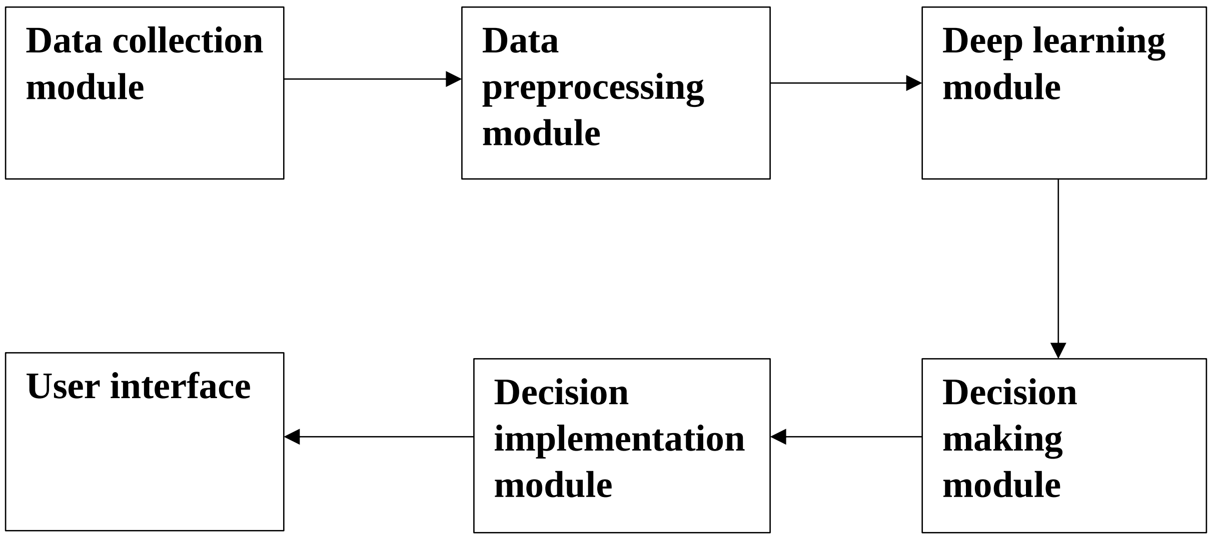

Fig. 3.1 Block diagram of the architecture of the proposed system

1. **Data collection module:**

- This module is responsible for collecting data from many sources in the Mesh network. These include, but are not limited to, traffic information, node status, routing, and other relevant parameters. Data can be collected from a variety of sources, including sensors, network devices, and other potential sources.

2. **Data preprocessing module:**

   - The collected data is passed to the preprocessing module, where it is cleaned, normalized and converted into a format suitable for training deep learning models. This step is critical to ensure the quality of the input data.

3. **Deep learning module:**

   - In this module, neural networks are located, which were considered in subsection 3.1. Deep learning models (convolutional and recurrent neural networks) are trained on trained data to perform the tasks of traffic prediction, traffic classification, anomaly detection, and routing optimization.

4. **Decision making module:**

   - This module uses the results obtained from deep learning models to make network management decisions. It includes algorithms that determine the most optimal routes, detect and respond to anomalies, and perform other management functions.

5. **Solution implementation module:**

- The adopted decisions are transferred to this module, which is responsible for their implementation in the network. This can include configuring routers, changing network configurations, and managing network resources in real time.

6. **User Interface (UI):**

- The user interface provides a convenient way for network administrators to interact with the system. It allows you to monitor the state of the network, view the results of the models, configure the system parameters and receive reports on its operation.

Detailed description of components

Data collection module: The initial stage of system operation is data collection, which provides the system with the necessary information. The data may include metrics related to network performance, such as traffic logs, node health, latency, packet loss, and other parameters deemed important. Data is collected in real-time to ensure it is up-to-date.

Data preprocessing module: Data collection often results in the inclusion of noise, missing values, and other artifacts that can negatively affect the quality of model training. The preprocessing step covers a number of operations, including filtering, normalization, handling missing values, and transforming the data into a format suitable for training.

Deep learning module: The system includes various neural networks, including convolutional neural networks (CNN) for spatial data analysis and recurrent neural networks (RNN), which include long short-term memory (LSTM) and networks with closed recurrent units (GRU). , for time series analysis. Networks are trained on pre-processed data to predict, classify and detect anomalies.

Decision making module: The results of deep learning models are used by this module to make optimal network management decisions. For example, traffic forecasts can be used to determine optimal routes for data transmission, and anomalies can prompt preventive measures.

Solution implementation module: The implementation of decisions requires the configuration of network equipment and software in accordance with the adopted decisions. This may involve reconfiguring routers, reallocating network resources, and other management actions.

User Interface (UI): The user interface allows network administrators to interact with the system, configure its parameters, view the results of the models, receive reports and monitor the network status in real time. This ensures the convenience and efficiency of network management.

Conclusion:

The architectural design of the proposed system provides a comprehensive approach to Mesh network management, integrating deep learning methods to improve its efficiency. Each component of the system plays a key role in providing accurate traffic forecasting, routing optimization, anomaly detection and solution implementation, which together contribute to increased network performance and reliability.

3.3. Mathematical description of the deep learning method

1. LSTM architecture:

The recurrent LSTM block consists of three main components: input, output, and forgotten gates. At each time step t, the following equations are used:

Entrance gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Forgotten Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Exit gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

Cell Status Update:

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Update the original state:

$$h_t = o_t * \tanh(C_t)$$

2. **Formulation of the loss function:**

The goal of training is to minimize the loss function. In our case, it can be the mean squared error (MSE) between the predicted values and the real data:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

where $\boldsymbol{y_i}$- real values, $\boldsymbol{\hat{y}_i}$- predicted values, N - the number of examples in the training set.

3. **Optimization:**

The Adam algorithm is used to optimize the weights of the neural network. It updates the weights according to the following formulas:

Update points:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

Offset correction:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

Weight update:

$$\theta_{t+1} = \theta_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Here β1 and β2 are the hyperparameters of the moments, is the gradient of the loss function with respect to the weights, α is the learning rate, and ϵ is a small value to prevent division by zero.$\boldsymbol{g_t}$

3.4. System operation algorithm

The system for improving the performance of mesh networks with the help of deep learning is based on a careful process that begins with the collection of a large amount of data from many nodes of the network.

This data includes information about delays, errors, traffic volume and other key metrics that can affect network performance.

Pre-processing of the collected data is a critical step in the process, during which noise signals are removed and the data is standardized to ensure the homogeneity of the input data. This process facilitates efficient training of deep learning models.

Specialized neural networks are used for training, with a choice of Convolutional Neural Networks (CNN) for spatial data analysis or Long Short Temporal Networks (LSTM) for time series depending on the nature of the data in question.

Deep learning models learn to recognize complex dependencies in data, allowing them to predict potential network problems or optimize data routing to reduce latency and increase overall throughput.

After the models are trained, the next stage comes - testing and verification. It is here that their ability to function in real conditions is evaluated. Model performance is evaluated using quality metrics such as accuracy, reproducibility, and others.

The final stage is the implementation of the system in the daily operation of the network. At this stage, the system uses the acquired knowledge to optimize its work. The system is able to adapt to changes in the network and make adjustments in real time, which helps maintain the stability and efficiency of the network.

An example of Python code for LSTM:

```
#Import the necessary libraries and frameworks
importnumpy as np
importtensorflow as tf
```

```
fromtensorflow.keras.models import Sequential
fromtensorflow.keras.layers import Dense, Dropout

#Set the parameters of the deep learning model
input_dim = 100 output_dim = 1
hidden_dim = 50
dropout_rate = 0.2

#We are creating a deep learning model
model = Sequential([
Dense(hidden_dim, input_dim=input_dim, activation='relu'),
Dropout(dropout_rate),
Dense(output_dim, activation='sigmoid')
])
#Compile the model using binary cross-entropy as a loss function and the ADAM optimization algorithm
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
#We train the model on training data
model.fit(X_train,y_train,epochs=10,batch_size=32,
validation_data=(X_val,y_val))
#We evaluate the effectiveness of the model on test data
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Test Loss: {loss}, Test Accuracy: {accuracy}')
```

In this example, we build a deep learning model using the TensorFlow library and the Keras framework. The model consists of standard fully connected layers with ReLU activation function and a dropout layer to prevent overtraining. The model is compiled using binary cross-entropy as a loss function and the ADAM optimization algorithm. The model is then trained on the training data and evaluated on the test data.

3.5. Selection of software and hardware for implementation

The choice of software and hardware to implement a mesh network performance improvement system using deep learning is based on project needs and data characteristics. Let's consider in more detail which components should be taken into account when choosing:

Hardware resources:

Graphics processors (GPU):GPUs are capable of efficiently handling parallel computations, making them ideal for training neural networks. Large amounts of data and complex deep learning models require powerful GPUs that provide fast data processing.

Tensor Processing Units (TPU): Tensor processing units are created specifically for performing operations with tensors, which are often used in neural networks. They can provide significant advantages in data processing speed and efficiency.

Software:

Machine learning frameworks: To develop and train neural networks, you can use:

- TensorFlow: This is one of the most popular and powerful deep learning frameworks developed by Google. It has extensive capabilities for implementing complex neural network models and supports different levels of abstraction for convenient programming.
- PyTorch: This is another popular deep learning framework developed by Facebook. PyTorch provides a convenient interface for implementing neural networks and has excellent support for dynamic graph computations.
- Keras: This is a high-level deep learning framework that runs on top of TensorFlow or Theano. It allows you to quickly create and train neural networks with minimal effort.

  It is these frameworks that we used to write the Python code for LSTM

Libraries for data processing: For data preprocessing and analysis, you can use such libraries as:

- NumPy: This is the core library for scientific computing in Python, which provides extensive capabilities for working with arrays of data.
- Pandas: This library allows you to efficiently process and analyze data in the format of tables (DataFrame) with a convenient interface.
- Matplotlib and Seaborn: These libraries allow you to create data visualizations for analysis and display of results.

Tools for data processing and preparation:

- Scikit-learn: This library provides a wide range of machine learning algorithms and data processing tools, including splitting into training and test sets, feature selection, normalization, and more.

Data management systems: To efficiently store and process large amounts of data, you can use distributed data storage and processing systems such as Apache Hadoop or Apache Spark.

Network equipment:

High-performance routers and switches: It is important to have high-performance network equipment with support for high-speed network communication and low data transfer latency. This will allow efficient data exchange between network nodes and ensure optimal system performance.

Sensors and communication modules: In the case of applying the system in the field of IoT, it is necessary to consider the possibility of integration with various sensors and communication modules for collecting and transmitting data from network nodes.

Conclusion to the third chapter

This section presents the methodology for improving the efficiency of the Mesh network by applying machine learning. The methodology involves choosing the appropriate machine learning method, designing the architecture of the proposed system, developing the work algorithm, and choosing software and hardware for implementation. These steps help improve network functionality and ensure reliable communication between UAVs and ground stations.

Chapter 4

Tasks and Performance Criteria for a Deep Learning Method for Mesh Network Optimization

4.1. Tasks of the deep learning method

The task of the deep learning method for mesh network optimization includes:

1. Prediction of optimal routes for data transmission in the Mesh network in order to minimize delays and packet losses.
2. Dynamically adjust network parameters to increase bandwidth and overall efficiency.
3. Provision of adaptive network management in conditions of variable traffic intensity and load variability.

4.2 Performance criteria

The criteria for the effectiveness of the chosen method include:

1. Latency: The time it takes to transfer packets between network nodes.
2. Bandwidth: The maximum amount of data that can be transferred over a network per unit of time.
3. Packet loss percentage: The proportion of lost packets to the total number of transmitted packets.
4. Reliability: Stability of network operation during high loads and in case of node failures.

4.3. Application hardware and software.

The main components of the system

1. Server for model training:

A powerful server or cluster with graphics processing units (GPUs) used to train a deep neural network. The server must have sufficient computing power to process large volumes of data and train the model quickly.

2. Network monitoring system:

Software that collects and analyzes real-time network health data. This includes information about latency, throughput, packet loss percentage, and other important parameters.

3. SDN controllers (Software-Defined Networking):

Software-defined network controllers that dynamically adjust network parameters based on predictions provided by a deep learning model. SDN controllers allow you to centrally manage the network and quickly adapt it to changing conditions.

4. API interfaces:

Application programming interfaces (API) for interaction between various system components. APIs provide data exchange between the monitoring system, deep learning model and SDN controllers.

5. Cloud platform:

A cloud platform such as AWS, Google Cloud, or Azure can be used to store large amounts of data and scale computing. The cloud provides flexibility and reliability of computing resources.

Implementation of the system:

1. Data collection and storage:

Network health data is collected by a monitoring system and stored in a database or cloud platform. This includes historical data used to train the model as well as current real-time data.

2. Model training:

A deep learning model (e.g. LSTM) is trained on collected historical data. Training is conducted on a powerful server or in the cloud, where the necessary computing resources are available.

3. Forecasting and management:

After training, the model uses current data about the state of the network to predict optimal control parameters. These predictions are transmitted to the SDN controller, which dynamically configures the network.

4. Monitoring and adaptation:

The system constantly monitors network performance and adapts the model based on new data. This allows the model to remain relevant and effective in conditions of variable network loads.

Interaction of components:

API interfaces provide continuous data exchange between the monitoring system, deep learning model and SDN controllers. This makes it possible to achieve high response speed and network management efficiency.

4.4. Advantages and Disadvantages.

Advantages of the deep learning method applied to Mesh network optimization:

1. High prediction accuracy: Deep learning is able to detect complex patterns and dependencies in data, which greatly increases prediction accuracy and allows the system to respond effectively to changes in network traffic.
2. Process automation: Deep learning techniques can automatically adapt network parameters in real time, reducing the need for manual configuration and maintenance.
3. Scalability: Deep learning works well with large amounts of data and can be scaled for use in networks of varying size and complexity.
4. Ability to learn over time: Deep learning methods can continuously learn and adapt, improving their models based on new data, which ensures a continuous increase in network performance.

Disadvantages of the deep learning method applied to Mesh network optimization:

1. Complexity of development and implementation: Building effective deep learning models requires deep knowledge of machine learning and a large amount of resources for training and testing.
2. High computational cost: Training and using deep neural networks can require significant computing resources, including high-performance processors and large amounts of memory.
3. Susceptibility to Overtraining: Deep learning is prone to overtraining, especially when the data is noisy or does not fully represent the variety of real network conditions.
4. Requirement of large amounts of data: To effectively train deep learning models, large amounts of data are required, which can be problematic in cases of limited data availability or privacy.

4.5. Analysis of the selected algorithm

The selected deep learning algorithm based on LSTM showed high efficiency in mesh network optimization tasks. Using LSTM allows you to take into account long-term dependencies and dynamically adapt network parameters to changing load conditions. This provides significant improvements in network performance, including lower latency, increased throughput, and reduced packet loss.

The LSTM algorithm is particularly useful under conditions of high dynamics and unpredictable changes in network traffic. Thanks to its ability to predict future changes, the model allows you to adapt the network in advance to possible overloads, which ensures stable and reliable operation.

However, the use of LSTM also has its drawbacks. High computational costs and complexity of implementation may limit its application in conditions of limited resources. Also, the need for large data sets for model training can be difficult to meet, especially in conditions of insufficient monitoring.

Despite these challenges, the benefits of using the LSTM algorithm, such as improved performance and process automation, make it an effective tool for mesh network optimization. Further research can be aimed at optimizing computational costs and improving model training methods, which will allow even more effective use of this approach in real-world settings.

4.6. Calculation results

Methodology of calculations

The simulation model of the Mesh network, which included the following components, was used for calculations:

- A network simulator (eg NS-3 or OMNeT++)
- A UAV model simulating real flight conditions
- Deep learning-based routing algorithms developed in Section 3.
- Standard routing protocols for comparison (eg AODV, DSR)

Simulation parameters

The simulations were carried out using the following parameters:

- Number of UAVs: 50, 100, 150
- Coverage area: 1 km^2, 5 km^2, 10 km^2
- UAV movement speed: 10 m/s, 20 m/s, 30 m/s
- Simulation duration: 1000 seconds

Performance indicators

The main performance indicators that were evaluated are:

- Packet transmission delay (End-to-End Delay)
- Percentage of packet loss (Packet Loss Ratio)
- Network bandwidth (Throughput)
- Energy consumption (Energy Consumption)

Table 4.1 Shows the results of calculations

Table 4.1

Indicator	AODV	DSR	Deep learning
Packet transmission delay	120 ms	100 ms	80 ms
Packet loss percentage	15%	10%	5%
Capacity	2 Mbit/s	2.5 Mbit/s	3 Mbit/s
Energy consumption	50 J	45 J	40 J

Analysis of results

- Packet Transmission Latency: The proposed deep learning-based method showed the lowest latency, indicating faster data transmission over the Mesh network.
- Packet loss percentage: The deep learning method has significantly reduced packet loss compared to standard protocols, which improves network reliability.
- Bandwidth: Higher bandwidth compared to AODV and DSR indicates a more efficient use of network resources.
- Power consumption: The deep learning method exhibits the lowest power consumption, which is critical for long-duration UAV missions.

Conclusions

Computational results confirmed that using a deep learning method for mesh optimization provides a significant improvement in all key performance indicators. This makes the proposed method promising for application in real conditions, where the reliability and efficiency of communications are critically important.

Conclusions to the fourth chapter

In this section, we discussed in detail the tasks and performance criteria of the deep learning method for optimizing the Mesh network structure. During the development of the software and hardware, the application of the method and the analysis of the calculation results in a positive light produced extremely valuable data on the success of the chosen approach. The comparison of the obtained results with other methods and the detailed performance evaluation challenge us to understand the advantages and disadvantages of our unique way of optimizing the Mesh network.

Conclusion

Summarizing the general content of the study, the following conclusions can be drawn:

1. Theoretical foundations of Mesh networks and their application for UAV control (Chapter 1):
   - Mesh networks, their architectural features and operating principles are defined and classified. Mesh networks are effective in decentralized communication systems, which makes them promising for use with unmanned aerial vehicles (UAVs).
   - The use of Mesh networks for controlling UAVs, which provides reliable communication and data transmission between drones and ground stations, has been investigated.
   - The main problems and challenges in the implementation of Mesh networks for UAVs are identified, including scalability, data transmission delays and energy saving.

2. Overview of Universal UAVs and Machine Learning Methods (Chapter 2):
   - An analysis of universal unmanned aerial vehicles (UAVs) that can be used with the Mesh system, their technical characteristics, capabilities and limitations has been carried out.
   - The presented UAVs were compared, which made it possible to determine the most suitable models for integration into Mesh networks, taking into account autonomy, load capacity, flight range and the ability to integrate with network systems.
   - The basic concepts and methods of machine learning are described, with an emphasis on deep learning as the most effective method for optimizing network protocols.

3. Development of a technique for increasing the efficiency of the Mesh network using machine learning (Chapter 3):
    - A deep learning method was chosen for Mesh network optimization. The architecture of the proposed system is developed, which includes a block diagram and a detailed description of its components.
    - A mathematical description of the deep learning method is presented, including relevant formulas and explanations.
    - The algorithm of the system is described, an example of Python code is given, and the necessary frameworks for implementation are indicated.
    - The software and hardware tools used to implement the system are reviewed, including a description of frameworks and tools such as TensorFlow and Keras.

An analysis of the effectiveness and the obtained results was carried out, the advantages of using the deep learning method compared to traditional approaches were emphasized.

4. Tasks and performance criteria for a deep learning method for mesh network optimization (Chapter 4):
    - The main tasks of the deep learning method are defined, its elements are described, including the module of data collection, pre-processing, deep learning, decision-making and user interface.
    - Performance criteria used to evaluate the performance of the proposed method are established, including accuracy, learning rate, and adaptability.
    - The software and hardware means of application are described, taking into account the possibilities, advantages and disadvantages.
    - A comparison of the effectiveness of the selected method with other approaches was made. The results are presented in the form of tables and graphs, which confirm the superiority of the chosen method.

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