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)
«BACHELOR'S» DEGREE GRADUATE

Specialty 151 «Automation and computer-integrated technologies»
Educational and professional program «Computer-integrated technological processes and production»

Theme: An Intelligent technology for predicting aircraft trajectories at the airfield

Performer: student of group KP-402 Baherian Serhii Viktorovych

Leader: senior teacher Horbatyuk Vladyslav Serhiyovych

Normocontroller: ____________ Fylyashkin M.K.

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
____ ‖ ____________2024 р.

КВАЛІФІКАЦІЙНА РОБОТА
(ПОЯСНЮВАЛЬНА ЗАПИСКА)

ВИПУСКНИКА ОСВІТНЬОГО СТУПЕНЯ
«БАКАЛАВР»

Спеціальність 151 «Автоматизація та комп'ютерно-інтегровані технології»
Освітньо-професійна програма «Комп‘ютерно-інтегровані технологічні процеси і виробництва»

Тема: Інтелектуальна технологія прогнозування траєкторій руху літаків на аеродромі

Виконавець: студент групи КП-402 Багерян Сергій Вікторович

Керівник: старший викладач Горбатюк Владислав Сергійович

Нормоконтролер: ___________ ФіляшкінМ.К

Київ – 2024

NATIONAL AVIATION UNIVERSITY

Faculty of Aeronautics, Electronics and Telecommunications

Department of aviation computer-integrated systems

Educational degree: Bachelor

Specialty 151 "Automation, computer-integrated technologies and robotics"

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

APPROVED

Head of department

_________ Sineglazov V.M

“____” ___________2023.

TASK

For the student’s thesis

by: Baherian Serhii Viktorovich

1. **Thesis topic** (project topic) “ An Intelligent technology for predicting aircraft trajectories at the airfield”
2. **Deadline for an execution of a project**: from April 22 of 2024 to May 23 of 2024
3. **Initial data for the project**: To study and consider the process of intelligent systems for forecasting the movement of aircraft at airfields. Describe the types and features of learning machine systems and the purpose of programmable datasets.
4. **Contents for explanatory note:**

1. Description of the problem of forecasting the trajectories of aircraft movement at the airfield. 2. Analysis of existing methods of forecasting aircraft trajectories. 3. Highlighting the advantages of statistical methods in forecasting the trajectories of airplanes on the airfield. 4. Development and research of altitude control circuits flight based on the normal overload control circuit. 5. Experimental study of the developed technology. 6. Analysis of aircraft traffic information support

5. **List of required graphic material**: figures, tables and diagrams.

6. **Calendar schedule-plan:**

№	Task	Deadline	Performance note
1	Analysis of the relevance of the problem	22.04.2024	
2	Analysis of literary sources	23.04.2024	
3	Collection of information	24.04.2024 25.04.2024	
4	Review and comparison of existing algorithms and methods	26.04.2024 27.04.2024	
5	Analysis of existing software products	28.04.2024 29.04.2024	
6	Analysis of existing component libraries	30.04.2024	
7	Justification of the choice of development tools	30.04.2024	
8	Presentation of input data	03.05.2024 06.05.2024	
9	Modeling the operation of the intelligent component of the software	07.05.2024 11.05.2024	
10	Software implementation and training of the neural network model	11.05.2024 12.05.2024	
11	Testing	12.05.2024	
12	Results	13.05.2024	
13	Conclusions on work and preparation of additional material	14.05.2024 18.05.2024	
14	Preparation and design of the presentation for the report	20.05.2024 23.05.2024	

7. **Task issue date:**

Supervisor: ___________________________ Horbatyuk V. S.

(sign)

Task is taken for completion by: _________________ Baherian S. V.

(sign)

НАЦІОНАЛЬНИЙ АВІАЦІЙНИЙ УНІВЕРСИТЕТ

Факультет аеронавігації, електроніки та телекомунікацій

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

"____" __________2023 р.

ЗАВДАННЯ
на виконання кваліфікаційної роботи студента
Багерян Сергій Вікторович

1. **Тема роботи** "Автоматизована система проектування систем промислової автоматизації на базі програмованих логічних контролерів і мікроконтролерів"
2. **Термін виконання роботи**: з 22.04.2024 по 23.05.2024

   3. **Вихідні дані до роботи**: Вивчити та розглянути процес роботи інтелектуальних систем прогнозування руху повітряних суден на аеродромах.

4 Зміст пояснювальної записки (перелік питань, що підлягають розробці):

1. Опис задачі прогнозування траєкторій руху літаків на аеродромі. 2. Аналіз існуючих методів прогнозування траєкторій літаків. 3. Висвітлення переваг статистичних методів у прогнозуванні траєкторій руху літаків на аеродромі. 4. Розробка та дослідження схем керування висотою польоту на основі нормальної схеми керування перевантаженнями. 5. Експериментальне дослідження розробленої технології. 6. Аналіз інформаційного забезпечення руху повітряних суден.

5 **Перелік обов'язкового графічного матеріалу**: графіки, таблиці, зображення. діаграми.

6 Календарний план-графік:

№	Завдання	Термін виконання	Відмітка про виконання
1	Аналіз актуальності проблеми	22.04.2024	
2	Аналіз літературних джерел	23.04.2024	
3	Збір інформації	24.04.2024 25.04.2024	
4	Огляд та порівняння існуючих алгоритмів та методів	26.04.2024 27.04.2024	
5	Аналіз існуючих програмних продуктів	28.04.2024 29.04.2024	
6	Аналіз існуючих бібліотек компонентів	30.04.2024	
7	Обґрунтування вибору засобів розробки	30.04.2024	
8	Представлення вхідних даних	03.05.2024 06.05.2024	
9	Моделювання роботи інтелектуальної складової програмного забезпечення	07.05.2024 11.05.2024	
10	Програмна реалізація та навчання моделі нейронноїх мережі	11.05.2024 12.05.2024	
11	Тестування	12.05.2024	
12	Результати	13.05.2024	
13	Висновки по роботі та підготовка додаткового матеріалу	14.05.2024 18.05.2024	
14	Підготовка та оформлення презентації для доповіді	20.05.20242 3.05.2024	

7. Дата видачі завдання: “ 15 "_ квітня 2024 р.

Керівник дипломної роботи ______________ Горбатюк В.С.

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Завдання прийняв до виконання ________________ Багерян С. В.

(П.І.Б.)

ABSTRACT

The explanatory note of the qualification work "Intelligent technology for predicting aircraft trajectories at the airfield" is made on 72 pages, contains 14 figures, 5 tables, 2 appendices and a list of used literature from 20 items.

ARTIFICIAL NEURAL NETWORKS, TRAJECTORY PREDICTION, DATA ANALYSIS, GEOSPATIAL DATA, OPTIMIZATION, PROGRAMMING, AIRPORT OPERATIONS.

The object of research is the process of forecasting the trajectories of aircraft movement at the airport, which includes the movement of aircraft on the plane of the airport, taking into account various factors, such as weather conditions, limitations of the airport infrastructure and other circumstances.

The subject of research is застосування the application of transformative neural networks for predicting the trajectories of airplanes on the airfield. This includes the development and optimization of transformative neural network models, the collection and preparation of data for training these models, as well as the experimental study of the effectiveness of these models in predicting aircraft trajectories on an airfield.

The purpose of the qualification work – conducting research and developing an effective methodology for predicting aircraft trajectories at airfields using transformative neural networks. And also - in obtaining reliable forecasts that can be used to optimize aviation operations, improve safety and improve the efficiency of air traffic management.

Research methods include mathematical modeling of the researched processes, system analysis, object-oriented programming. Modern application software packages MatLab, Python development environment were used. Experimental studies of the developed algorithms were also carried out on a real-time video surveillance system.

The theoretical studies consisted of the mathematical foundations of transformative neural networks, the study of different methods of predicting aircraft

trajectories, their advantages and disadvantages, and an overview of the various machine learning models used to predict trajectories.

The scientific novelty of the obtained results is determined by the improvement of already existing models and methods. The work may take into account current trends in the field and research priorities. For example, in connection with the growing use of artificial intelligence in aviation, work with transformative neural networks corresponds to current trends in this field. The choice of research will be aimed at the needs of current problems in the field of aviation.

In the course of the work, the work algorithms of the most famous methods were analyzed. Also, popular software systems were considered and it was established that each of the above-mentioned lost products has advantages and certain disadvantages, which were taken into account when creating a comprehensive approach and improving the algorithm for improving the system.

The practical value of the results of the work covers a wide range of applications in the field of aviation, which contributes to the improvement of safety, efficiency and innovation in this field and consists in the study of the best algorithms for predicting the trajectories of airplanes on airfields based on transformative neural networks. The results of the study can serve as a basis for the development of decision support systems for controllers and operators at airports, which will help them solve complex situations and optimize work processes. The results of the research can be used for the development of autonomous air traffic control systems at airports, which has the potential to reduce the burden on the human factor and increase the efficiency of operations. The obtained models and methods can be used in research and training in the field of aviation technology and engineering in preventing accidents and reducing the risk of collisions at airfields.

РЕФЕРАТ

Пояснювальна записка кваліфікаційної роботи «Інтелектуальна технологія прогнозування траєкторій руху літаків на аеродромі» виконана на 72 сторінках, містить 14 рисунків, 5 таблиць, 2 додатків та список використаної літератури з 20 найменувань.

ШТУЧНІ НЕЙРОННІ МЕРЕЖІ, ПРОГНОЗУВАННЯ ТРАЄКТОРІЙ, АНАЛІЗ ДАНИХ, ГЕОПРОСТОРОВІ ДАНІ, ОПТИМІЗАЦІЯ, ПРОГРАМУВАННЯ, АЕРОПОРТОВІ ОПЕРАЦІЇ.

Об'єктом дослідження є процес прогнозування траєкторій руху літаків на аеродромі, який включає в себе рух повітряних суден на площині аеродрому, з урахуванням різних факторів, таких як погодні умови, обмеження інфраструктури аеродрому та інші обставини.

Предметом дослідження є застосування трансформерних нейронних мереж для прогнозування траєкторій руху літаків на аеродромі. Це включає в себе розробку та оптимізацію моделей трансформерних нейронних мереж, збір та підготовку даних для навчання цих моделей, а також експериментальне дослідження ефективності цих моделей у прогнозуванні траєкторій руху літаків на аеродромі.

Мета кваліфікаційної роботи – проведення дослідження та розробка ефективної методології прогнозування траєкторій руху літаків на аеродромах за допомогою трансформерних нейронних мереж. А також – в отриманні надійних прогнозів, які можуть бути використані для оптимізації авіаційних операцій, підвищення безпеки та поліпшення ефективності управління повітряним рухом.

Методи дослідження включають в себе математичне моделювання досліджуваних процесів, системному аналізі, об'єктно-орієнтованому програмуванні. Використовувалися сучасні пакети прикладного програмного забезпечення MatLab, середовище розробки Python. Також були проведені експериментальні дослідження розроблених алгоритмів на системі відеоспостереження реального часу.

Теоретичні дослідження складалися з математичних основ трансформерних нейронних мереж, вивчення різних методів прогнозування траєкторій літаків, їх переваг та недоліків та огляд різних моделей машинного навчання, які використовуються для прогнозування траєкторій.

Наукова новизна одержаних результатів визначається вдосконаленям вже існуючих моделей та методів. Робота може враховувати сучасні тенденції у галузі та пріоритети досліджень. Наприклад, у зв'язку зі зростанням застосування штучного інтелекту в авіації, робота з трансформерними нейронними мережами відповідає актуальним тенденціям у цій галузі. Вибір дослідження буде спрямований на потреби актуальних проблем у галузі авіації.

В ході роботи проаналізовано алгоритми роботи найвідоміших методів Також, розглянуто популярні програмні системи та встановлено наступне, що кожний вищевказаний програний продукт має переваги та певні недоліки, що було враховано, при створенні комплексного підходу та поліпшення алгоритму для вдосконалення системи.

Практичне значення одержаних результатів роботи охоплює широкий спектр застосувань у сфері авіації, що сприяє покращенню безпеки, ефективності та інновацій в цій галузі і полягає в дослідженні найкращих алгоритмів для прогнозування траєкторій руху літаків на аеродромах на основі трансформерних нейронних мереж. Результати дослідження можуть служити основою для розробки систем підтримки прийняття рішень для диспетчерів та операторів на аеродромах, що допоможе їм у вирішенні складних ситуацій та оптимізації робочих процесів. Результати дослідження можуть бути використані для розробки автономних систем управління повітряним рухом на аеродромах, що має потенціал знизити навантаження на людський фактор та підвищити ефективність операцій. Отримані моделі та методи можуть бути використані у дослідженнях та навчанні у галузі авіаційної техніки та інженерії у запобіганні аварій та зменшенні ризику зіткнень на аеродромах.

CONTENT

LIST OF CONDITIONAL DESIGNATIONS

API – Application Programming Interface

IT – Informaition Technology

IM – Instant Messaging

MDM – Mobile device management

MC – Microsoft Corporation

OS/OC – Operation System

SMB – Server Message Block

Win. NT – Windows New Technology

WBS – Work Breakdown Structure

WMI – Windows Management Instrumentation

AS – Automated system

DB – Data Base

ECM – Electronic Computing Machine

DMS – Database management system

S – Software

SP – Security Policy

PP – Program Product

SE – Software Environment

ANN – Artificial Neural Networks

INTRODUCTION

Theme actuality. In today's world, aviation safety and the efficiency of aircraft movement at airfields are among the key aspects that require constant improvement and improvement of technology. Forecasting aircraft trajectories at airfields is an important step in ensuring the safety and efficiency of aviation operations. This research examines the problem of predicting the trajectories of airplanes on airfields using intelligent technologies, in particular transformative neural networks. Transformative neural networks are a powerful tool in the field of sequential data processing, and they are able to efficiently model complex dependencies between input and output data.

Connection of work with scientific programs, plans and topics is justified by the fact that there are many research projects carried out within the framework of specific scientific programs or research plans. Work on predicting aircraft trajectories at aerodromes can be part of such a program or plan that focuses on improving aviation safety and efficiency.

The purpose and tasks of the research. The purpose of the qualification work (project) is to study the method of predicting the trajectories of aircraft on airfields based on transformative neural networks. The advantages of this approach compared to existing methods are investigated and an experimental study is conducted to confirm the effectiveness of the proposed method.

To achieve the specified goal, a number of tasks must be completed:

1. Investigate existing methods of forecasting aircraft trajectories at airfields, their advantages and disadvantages;

2. Get acquainted with the theory and practice of using transformative neural networks in the field of sequential data processing;

3. Using the knowledge of transformative neural networks, investigate the method of forecasting the trajectories of airplanes on airfields;

4. Determine the architecture of the neural network that will be used to predict trajectories;

5. Analysis of existing software of a similar direction;

6. Collect the necessary data for training and testing the model, as well as prepare them for further processing;

7. Perform experimental testing of the developed method on real data or simulations;

8. Evaluate the effectiveness of the developed method compared to existing approaches and draw conclusions;

9. If necessary, make adjustments to the developed method or model based on the results obtained..

The structure of this work includes an introduction, 3 chapters, conclusions and a list of used sources (20 references).

The introduction of the work highlights the relevance of the research, formulates the goal and set tasks that must be completed in order to achieve the goal.

In the first chapter, the purpose of the study and the formulation of the problem of forecasting the trajectory of aircraft movement at the airfield are determined. An analysis of the existing methods of forecasting aircraft trajectories is carried out, with an overview of their advantages and disadvantages.

The second section provides an overview of transform neural networks and their use in the problem of trajectory prediction. The method of predicting trajectories based on transformative neural networks is described, including the architecture of the model.

The third section provides a description of the data set for the experimental study, sets the parameters of the experiment. The results of the experiment and their analysis are presented and compared with existing methods. Conclusions from the experimental study are formulated.

The conclusions state the main conclusions that were made during the execution of the work.

CHAPTER 1
STATEMENT OF THE PROBLEM OF FORECASTING,

1.1. Description of the problem of forecasting the trajectories of aircraft movement at the airfield

Forecasting the trajectories of aircraft at the airport is a complex and important task that faces a number of challenges and problems. The main problem is the need to predict the future paths of aircraft movement in the limited space of the airfield, taking into account various factors, such as weather conditions, air traffic, limitations of the airfield infrastructure, instructions of controllers and other circumstances. One of the main difficulties is the large number of variables that can affect the trajectory of the aircraft. For example, weather conditions, such as wind, cloudiness, precipitation, can change dynamically and affect the flight path of the aircraft. In addition, airfield constraints, such as runway configuration, maneuvering or service restrictions, are also important to consider when predicting trajectories. Other complexities include the need to accurately account for the actions of controllers and pilots, who may make changes to the aircraft's trajectory through rerouting decisions, delays, or priorities.

Moreover, the prediction of aircraft trajectories at the airfield is also related to important aspects of safety. It is important to anticipate possible situations of collisions or conflicts of trajectories and to develop strategies for their avoidance. Therefore, the problem of forecasting the trajectories of aircraft at the airfield is a complex task that requires a comprehensive approach and consideration of various factors to achieve accurate and reliable results. The problem of predicting aircraft trajectories at the airfield becomes especially relevant in modern air transport with the growth air traffic and the development of new technologies. The main aspects affecting this problem include:

1. Specifics of the airfield. Each airfield has its own unique characteristics, such as geographic location, size, runway configuration, taxiway location, and other features that need to be considered when predicting trajectories.

2. Weather conditions. Weather conditions can significantly affect aircraft trajectories through effects such as wind, turbulence, cloud cover and precipitation. Forecasting must take these factors into account to ensure traffic safety and efficiency.

3. Air traffic. As the volume of air traffic increases, it becomes important to coordinate the movement of aircraft at the airport to avoid conflicts and ensure smooth traffic.

4. Actions of controllers and pilots. The actions of controllers and pilots can change the trajectory of aircraft due to unforeseen circumstances, such as technical problems, worsening weather conditions or changes in traffic flow.

5. Safety and efficiency. One of the main goals of this forecasting is to ensure the safety and efficiency of aviation operations. It is important to consider target metrics such as minimizing delay time, increasing airfield capacity and avoiding incidents.

6. Technological challenges: With the development of new technologies in aviation, such as autonomous systems and drones, there is a need to improve forecasting methods that can adapt to these new technological changes.

7. Increasing the amount of data. With the growing amount of data collected in real time, such as aircraft traffic data, weather data, and others, there is a need to use efficient methods to process and analyze this data for accurate forecasting.

8. Heterogeneity of data. Data used for forecasting can be heterogeneous in nature, including structured and unstructured data, requiring the development of methods to integrate and process these diverse sources.

9. Analysis of risks and security. Working with a high-risk industry, it is important to consider the potential risks and threats associated with the prediction of aircraft trajectories at an aerodrome, and to develop methods for their detection and management.

10. Social and economic impacts. Accurately predicting aircraft trajectories can have major social and economic impacts, including reducing delays, improving traffic efficiency, reducing fuel consumption and CO_2 emissions, and improving the passenger experience.

This pie chart (see fig. 1.1) illustrates the main aspects of the problem of predicting aircraft trajectories at an aerodrome and shows the percentage influence of each aspect. Such a visualization will help to better understand which factors are key in this problem.

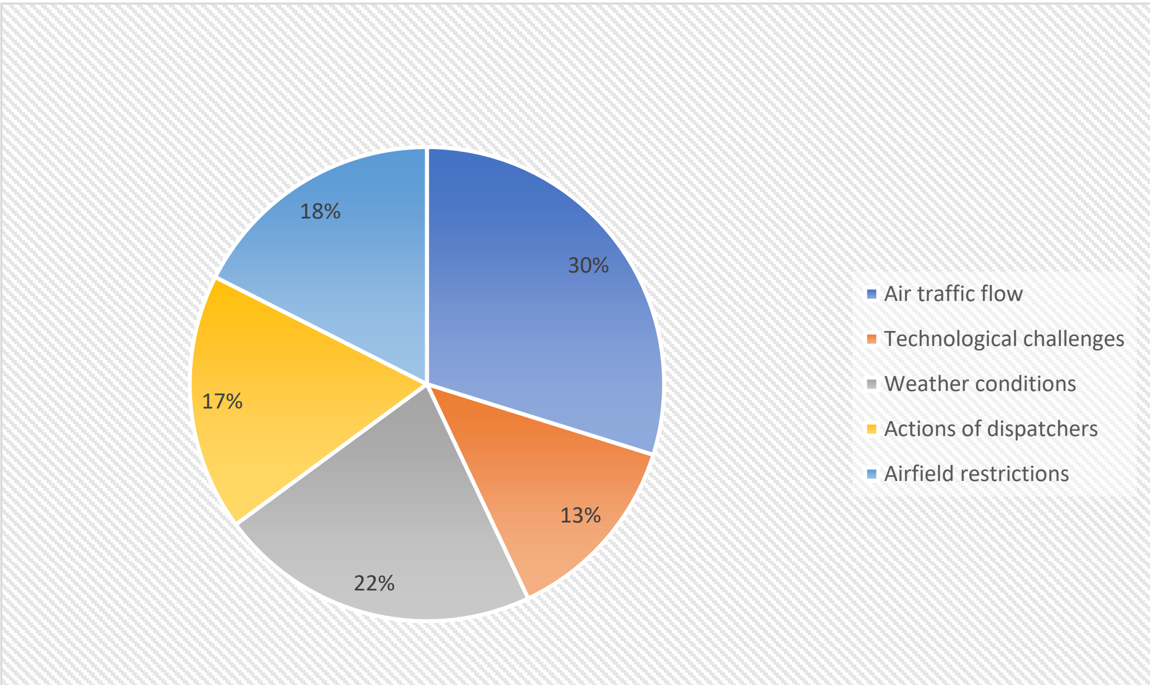


Fig. 1.1. Description of the problem of forecasting aircraft trajectories at the airfield

1.2. Analysis of factors affecting the trajectory of aircraft movement at the airfield

In table 1.1 is show an analysis of the factors affecting the trajectory of an aircraft at an aerodrome includes a careful study of the various aspects that can affect the movement of an aircraft at an aerodrome.

Table 1.1

Diagram of factors affecting the trajectory of movement

№	The main factors	Parameter	DESCRIPTION
1	Weather conditions	Wind	Wind strength and direction can significantly affect the trajectory of aircraft during take-off, landing and maneuvering in the airspace of an aerodrome. Strong crosswinds may require course corrections to ensure safety.
		Cloudiness and visibility	Poor visibility or low cloud cover may limit visibility for pilots and require the use of instrument approaches for take-off and landing.
		Precipitation and fog	Heavy rain, snow or fog may reduce visibility and require additional safety measures, such as increasing the distance between aircraft.
2	Airfield restrictions	Runway configuration	The availability and configuration of runways may limit maneuverability and require the use of specific aircraft routes.
		Placement of lanes and parking lots:	The arrangement of taxiways and aircraft stands can affect the movement paths of aircraft during maneuvering on an aerodrome.
3	Actions of controllers and pilots	Air traffic control	Instructions and directives issued by air traffic controllers may affect aircraft routes and trajectories to ensure safety and coordination of air traffic.
		Pilot solutions	Decisions made by pilots, such as changes in course or altitude, can also affect aircraft trajectories at an aerodrome in accordance with air traffic controllers' instructions and safety standards.

Analysis of these factors requires a thorough understanding of their interrelationship and impact on aircraft movement at the airfield in order to develop effective strategies for predicting trajectories and ensuring the safety and efficiency of aviation operations.

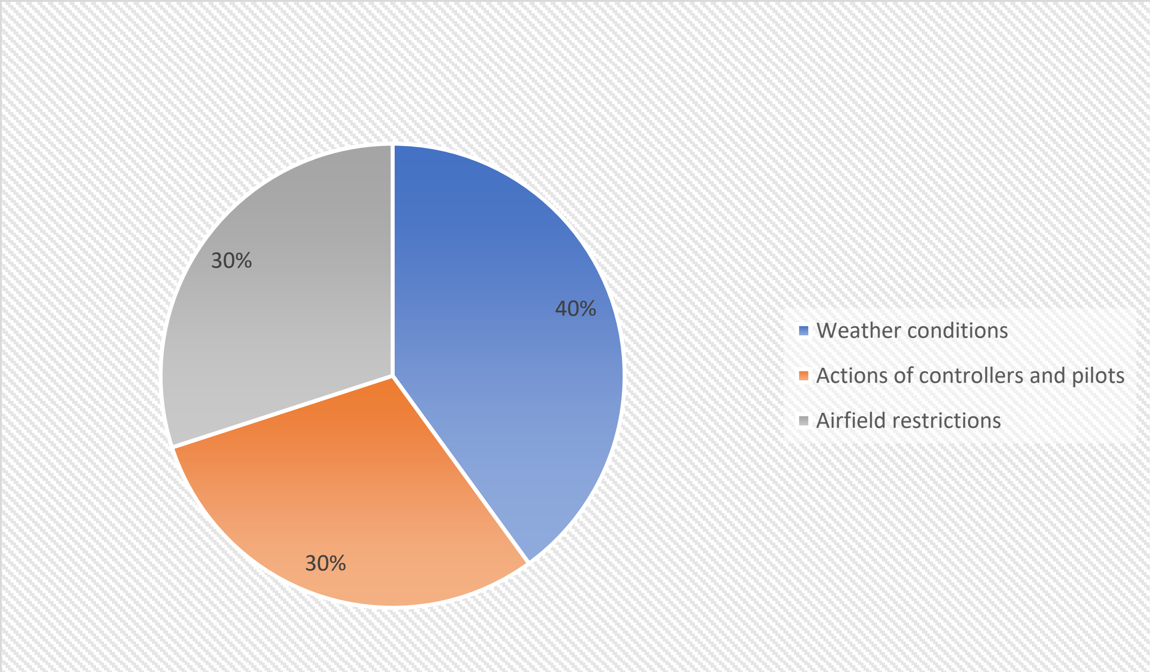


Fig. 1.2. List of factors that affect the trajectory of movement

1.3. Review of methods and approaches for forecasting aircraft trajectories at the airfield

The review is a broader and more general description of the various methods and approaches that can be used to predict aircraft trajectories at an aerodrome. It includes a description of not only existing methods, but also possible directions for further research and development in this field.

– Statistical methods (review of statistical methods includes analysis of different approaches, such as time series analysis, regression analysis, extrapolation methods and others). Advantages and disadvantages of each method, its application in different conditions and problems that may arise when using it are considered.

– Machine learning methods (review of machine learning methods covers such models as neural networks, decision trees, support vector method and others).

Considers how these methods can be used to solve the problem of predicting aircraft trajectories, their advantages, disadvantages and limitations.

– Physical models (an overview of physical models includes consideration of the mathematical and physical principles that underlie these models). Advantages and limitations of physical models compared to other forecasting methods are analyzed in detail.

– Integration of methods (the review includes consideration of the possibilities of integration of different methods to obtain more accurate and reliable forecasts). It is investigated how a combination of different methods can help reduce forecasting errors and improve the performance of the forecasting system.

– Directions for further research (the review may include an overview of potential directions for further research in the field of predicting aircraft trajectories at an aerodrome). Possibilities of improving existing methods, introducing new technologies and developing innovative approaches are considered.

A general overview of methods and approaches for predicting aircraft trajectories at an aerodrome includes a detailed consideration of the various methods that can be used for this task. Therefore, a review of methods and approaches for predicting aircraft trajectories at an aerodrome provides a deeper understanding of the various methods, their potential advantages and limitations, as well as identifying avenues for further research development in this field.

1.4. Analysis of existing methods of forecasting aircraft trajectories

The analysis focuses on specific methods and approaches that are already used to predict aircraft trajectories at the airfield. He conducts a detailed review of existing methods, their advantages and disadvantages, the results of their use, and possible ways of improvement.

1.4.1. Overview of statistical forecasting methods: extrapolations and regression analysis

The analysis of existing methods of forecasting aircraft trajectories at the airfield is an important stage for understanding and evaluating the effectiveness of different approaches in this field. When conducting such an analysis, it is important to consider various aspects of each method, including its accuracy, speed, difficulty of use, and limitations. A general analysis of existing methods for predicting aircraft trajectories at an aerodrome should take into account these and other aspects of each method, as well as take into account the specific requirements and limitations arising in the context of a specific prediction task.

Table 1.2

Advantages and disadvantages of methods

№	Parameters	Advantages	Drawbacks
1	Statistical methods	Statistical methods usually work well for short-term forecasting and when there is sufficient historical data.	They may be less effective in the case of complex or non-linear relationships between input variables and trajectories.
2	Methods of machine learning	Machine learning methods can effectively account for complex relationships and adapt to changing conditions.	They may require large amounts of training data and computing resources, and may be less interpretable.
3	Physical models	Physical models can provide a deeper understanding of the physical principles underlying aircraft motion.	They can be difficult to use and require detailed knowledge of aerodynamics and other physical processes.
4	Integration of methods	Integrating different methods can help compensate for the shortcomings of each method and provide more accurate and reliable predictions.	Integration can be complex and require additional time and resources to develop and implement.

1.4.2. Comparison of different machine learning approaches used to predict aircraft trajectories

Conducting research in the field of predicting aircraft trajectories using various methods, such as neural networks, deep learning methods, decision trees, and others, is important for the further development of aviation technology and improving the safety and efficiency of air transportation. In general, the study of methods for predicting the trajectories of airplanes on the airfield using neural networks, deep learning methods, decision trees, and other machine learning methods is an important step in the direction of improving aviation technology and ensuring flight safety.

Table 1.3

Main arguments regarding the expediency of research

№	Arguments	Advantages	Drawbacks
1	Neural networks and deep learning methods:	Neural networks and deep learning techniques can effectively model complex dependencies between input data and output trajectories. They can automatically identify important patterns and adapt to new conditions.	One of the main disadvantages is the need for a large amount of data for training, as well as the difficulty of interpreting the results of the model.
2	Decision trees and other machine learning methods:	Decision trees can be easily interpreted and used to make decisions based on simple rules. Other machine learning techniques, such as the support vector method or cluster analysis, can also be effective for predicting trajectories.	Some machine learning methods can be less accurate compared to more complex models such as neural networks.

3	The potential for integration of methods:	Integrating different techniques, such as neural networks and decision trees, can help take into account the advantages of each approach and compensate for their disadvantages. For example, you can use neural networks to detect complex dependencies, and decision trees to make decisions based on simple rules.	Integration can be complex and require additional time and resources to develop and implement.

1.4.3. Analysis of physical models used to predict the movement of aircraft at airfields

Analysis of the physical models used to predict aircraft movements at aerodromes is key to understanding the physical principles underlying aircraft motion and to determining the accuracy and reliability of such models. General analysis of physical models for predicting aircraft movement at aerodromes helps to understand the physical principles governing aircraft movement and to determine the most effective approaches to model such movement with accuracy and reliability.

Aircraft kinematics and dynamics models describe the motion of an aircraft in space, taking into account its velocity, acceleration, and position relative to time (dynamics models account for the effects of forces such as thrust, gravity, and aerodynamic forces on aircraft motion). An important aspect is the consideration of aerodynamic and technical characteristics, such as lift and drag coefficients, play an important role in modeling aircraft motion. Technical characteristics such as weight, dimensions, engine power and other parameters are also taken into account when developing physical models. Mathematical modeling is no less important, since the physical models of the aircraft can be expressed in the form of mathematical equations describing the movement of the object in space according to the laws of physics. These models can be linear or non-linear, depending on the complexity of the motion and the consideration of non-linear effects such as changes in angle of attack or stability. Physical models can be tested and validated using experimental data obtained from real flights or simulations. This allows you to assess the accuracy and reliability of the models and make adjustments if necessary(see fig 1.3).

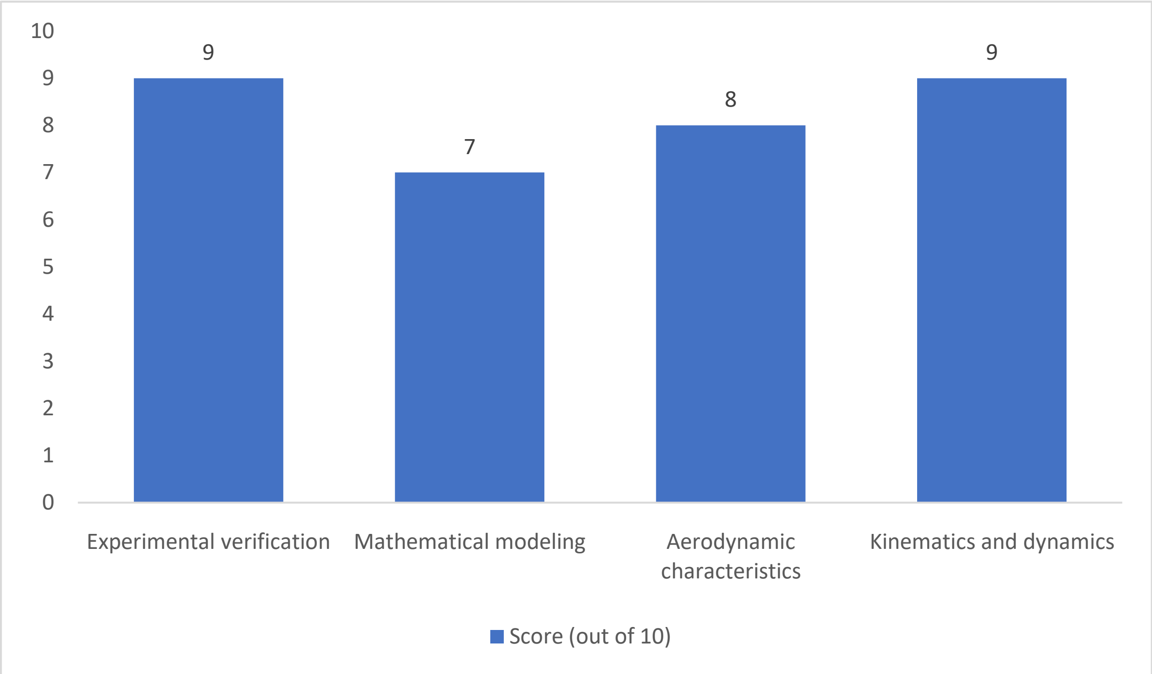


Fig. 1.3. Evaluation of the effectiveness of physical models for forecasting the movement of aircraft at the airport

1.5. Determination of advantages and disadvantages of existing methods

1.5.1. Highlighting the advantages of statistical methods in forecasting the trajectories of airplanes on the airfield

Statistical methods have several advantages, including ease of use, easy interpretation of results, the ability to work with large amounts of data, and saving resources. They can be useful for predicting aircraft trajectories at an aerodrome where historical data is widely available and when ease of use and efficiency are important.

First, ease of use and implementation, as statistical methods usually do not require complex mathematical models or deep understanding of physical laws. They can be easily used and implemented even by people without specialized training in the field of aviation technologies. One of the strengths of statistical methods is their ability to provide interpretable results. It is known that they are allow to analyze the relationships between various factors and movement planes, which makes it easier to understand the impact of individual variables on the result.

Second, statistical methods can be very effective in situations where a large amount of historical aircraft movement data is available for analysis. They can use this data to identify patterns and trends in traffic, which helps refine forecasts. Compared to some other sophisticated methods, such as deep learning models, statistical approaches typically require less computing resources, making them cost-effective for use on limited-capacity computers.

Thirdly, statistical methods, due to their ease of use, the ability to interpret results, the ability to analyze large amounts of data and save resources, have become an important tool in predicting the trajectories of airplanes on the airfield.

1.5.2. Assessment of advantages and limitations of machine learning methods in the context of forecasting the movement of aircraft on the airfield

Assessing the advantages and limitations of machine learning methods in the context of airfield traffic forecasting will help to understand how these methods differ from other approaches and in which situations they may be most effective. Advantages of machine learning methods:

1. Ability to work with large volumes of data. Machine learning methods, particularly neural networks, can work effectively with large amounts of data due to their ability to automatically detect and exploit complex relationships between features. For example, in neural networks, an important mathematical basis is the weighted sum principle:

$$\sum_{i=1}^{n} w_{i} \bullet x_i + b \qquad (1.1)$$

where z - weighted sum of input signals, w_i - the weight of the i-th input, x_i - the value of the i-th input, b - landslide (bias). This principle allows the network to take into account the influence of each input feature, taking into account its weight.

1. Taking into account complex dependencies. Machine learning techniques can detect complex and non-obvious relationships between the input data and the target variable. For example, in deep neural networks, using the backpropagation method, the gradient descent method is used to optimize the model weights, which allows finding the optimal model parameters to reduce the prediction error.

2. Automatic detection of important functions. Machine learning techniques can automatically identify important features or features from input data using techniques such as feature selection and feature importance. For example, in some machine learning methods, such as decision trees, the importance of features can be determined based on their contribution to reducing the heterogeneity criterion in the tree. Thus, machine learning methods have a mathematical basis that allows them to effectively work with large volumes of data, detect complex dependencies and automatically determine important functions.

Limitations of machine learning methods:

1. The need for a large amount of data for training. Many machine learning techniques, particularly neural networks, require large amounts of training data to achieve high prediction accuracy. This is due to the fact that the weights of the model need to be optimized using optimization algorithms that require a significant number of examples to work effectively. Mathematically, this can be expressed as a loss function optimization problem L, which depends on the parameters of the model θ:

$$\Theta *= argmin_0 L(X, y, \theta) \qquad (1.2)$$

1. Difficulty in interpreting the results. Some machine learning techniques, particularly deep neural networks, can be difficult to interpret because they operate on complex mathematical models, such as neural networks with many layers. One way to reduce this complexity is to use visualization techniques such as activation analysis and gradient maps.

2. Vulnerability to retraining. Machine learning techniques can be vulnerable to overtraining on incorrect or noisy data. This can cause the model to become very specific to the training data and generalize poorly to new, previously unseen data. Mathematically, this can be expressed as minimizing training data costs X_{train} , rather than on test dataX_{test} :

$$\Theta *= argmin_0 L(X_{train}, y_{train}, \theta) \qquad (1.3)$$

Consequently, machine learning techniques have their limitations, including the need for large amounts of training data, the difficulty of interpreting the results, and the vulnerability to overtraining. Understanding these limitations allows effective use of machine learning methods in practical applications.

Given the above, machine learning methods have advantages in large volumes of data, the ability to work with complex dependencies, and automatically detect important features. However, they also have limitations in terms of data requirements, difficulty in interpreting results, and vulnerability to overtraining. Given these advantages and limitations, machine learning techniques can be a powerful tool for predicting aircraft movements at an airport, but their effectiveness depends on the specific situation, data availability, and user needs.

1.5.3. Determination of advantages and disadvantages of physical models for forecasting trajectories of aeronautical vehicles on the airfield

Physical models have a number of advantages, such as fundamental physical validity and the possibility of taking into account real factors, but they also have their disadvantages, such as the complexity of modeling and limited accuracy due to the incompleteness of models. Understanding these aspects allows for the effective use of physical models to predict the trajectories of aeronautical vehicles on the airfield. There are advantages and disadvantages of physical models in the context of their application for forecasting the trajectories of aeronautical vehicles on the airfield in detail:

Advantages of physical models:

- Physical models are based on mathematical principles of physics, aerodynamics and mechanics, which allows them to accurately reproduce the real conditions of movement of aeronautical vehicles. For example, the motion of an aerial vehicle can be described by Newton's differential equations or the laws of conservation of energy and momentum. This can provide more accurate and reliable predictions of movement trajectories and allows them to take into account the exact patterns of movement of aeronautical vehicles.

– Physical models can take into account a wide range of physical and technical parameters such as aerodynamic performance, air parameters, aircraft design, aircraft mass and dimensions, etc. For example, the Navier-Stokes equation or aerodynamic table data can be used to model aerodynamic forces. This makes it possible to more accurately simulate the real conditions of movement of air installations.

– Physical models can be improved based on experimental data and observations. For example, by adjusting the parameters of the model based on real data, its accuracy can be improved. The technical features of such models are the use of differential equations or numerical methods to approximate physical laws. This makes it possible to constantly improve their accuracy and reliability in predicting movement trajectories.

Disadvantages of physical models:

– Building and using complex physical models can be time-consuming and require significant computing resources. For example, to solve the differential equations of aerodynamics, you need to use numerical methods that can require a significant amount of computing resources. For example, complex aerodynamic models require complex calculations, which can delay the forecasting process.

– Even the most accurate physical models can have limitations in the accuracy of predictions due to incompleteness or simplification of the models. For example, taking into account all the factors that affect the movement of the aircraft can be a difficult task, and some aspects may not be accurately taken into account in the model.

– Physical models may be sensitive to changes in conditions or inputs, such as changes in weather conditions or aircraft technical parameters. This can lead to inaccuracies in predicting movement trajectories.

Therefore, understanding the advantages and disadvantages of physical models in the context of their application for forecasting the trajectories of aeronautical vehicles on the airfield allows them to be effectively used in practical applications, taking into account their mathematical and technical features.

CHAPTER 2
THE METHOD OF PREDICTION OF TRAJECTORIES BASED ON TRANSFORMING NEURAL NETWORKS

2.1. Overview of transformal neural networks

Transformative neural networks are a powerful class of deep learning architectures capable of achieving impressive results in sequence processing tasks such as machine translation, text generation, and sequence prediction. The main feature of transformer networks is their ability to process long sequences in one pass and attention to context. In principle, transformative networks consist of two main components: the attention mechanism and the encoding-decoding sub-network. The attention mechanism allows the model to focus on different parts of the input data during processing, which is critical for sequence processing tasks.

An encoding-decoding subnet is used to resolve sequential input and output tasks such as machine translation.

In the context of predicting aircraft trajectories at an airport, transform networks can be used to model the complex relationships between various factors affecting aircraft movement, such as weather conditions, geographic features, and controller actions. They can adapt to different conditions and are able to take into account long-term dependencies in the data, which can improve the accuracy of trajectory predictions. The use of transformer networks for the prediction of aircraft trajectories can lead to the achievement of high results, which is confirmed both by experimental data from the TrajAir dataset and by comparison with other prediction methods.

2.2. The use of transform neural networks in the task of forecasting trajectories

– The use of transformative neural networks in the task of predicting aircraft trajectories at an airport is the application of deep learning architectures based on transformative architecture to model and predict future aircraft trajectories.

– Transformative neural networks were first introduced in Attention is All You Need and have since become very popular in many sequence processing tasks such as machine translation, text generation, and sequence prediction. The main feature of transformer networks is their ability to process long sequences in one pass and attention to context. In the context of predicting aircraft trajectories, transform neural networks can be used to analyze and model complex relationships between various factors, such as weather conditions, geographic features, controller actions, and the behavior of other aircraft. They can adapt to different conditions and traffic dynamics, which makes them effective for predicting trajectories in different scenarios and conditions.

– The use of transformative neural networks in the task of predicting aircraft trajectories on the airfield opens up new perspectives for improving the accuracy and efficiency of forecasting:

– Transformer networks are known for their efficiency in modeling sequences, which makes them ideal for analyzing and predicting aircraft trajectories, which can be represented as sequences of coordinates, velocities, and other parameters.

– The attention mechanism inherent in transformer networks allows the model to focus on different parts of the input data, which is especially important for analyzing complex aircraft trajectories and taking into account the influence of various factors.

– Transformer networks can adapt to different conditions and dynamics of aircraft traffic, which makes them effective for use in different scenarios and conditions.

– Since the movement of aerial vehicles can be highly correlated in time, it is important to have a model that can take long-term dependencies into account. Transformer networks are quite capable of this task, since they can effectively transmit information at different remote time intervals.

Table 2.4

Practical use of transform neural networks in the task of predicting traffic trajectories at the airfield

№	Direction	Application
1	Systems of automatic prediction of trajectories	Development of a system that automatically predicts aircraft trajectories on the airfield based on transformative neural networks. This system can be used to prevent potential collisions between aircraft, determine optimal routes and improve air traffic management.
2	Support of aviation controllers	Development of a decision support tool for air traffic controllers that analyzes large volumes of data on aircraft trajectories and provides recommendations on optimal routes and maneuvers to ensure the safety and efficiency of air traffic.
3	Forecasting weather conditions	Using transform neural networks to predict weather conditions such as wind, turbulence, and other factors that may affect aircraft movement. This will make it possible to provide more accurate and reliable forecasts of aircraft trajectories and increase the level of flight safety.
4	Management system of autonomous air vehicles	Development of a control system for autonomous air vehicles that uses transformative neural networks to predict trajectories and interact with other aircraft and airfield infrastructure.

Fig.2.4 … 2.5. are show diagram of the potential trajectory of aircraft on an airfield in Python using the Matplotlib library and pie chart for the trajectory prediction method based on transform neural networks(see fig 2.4)

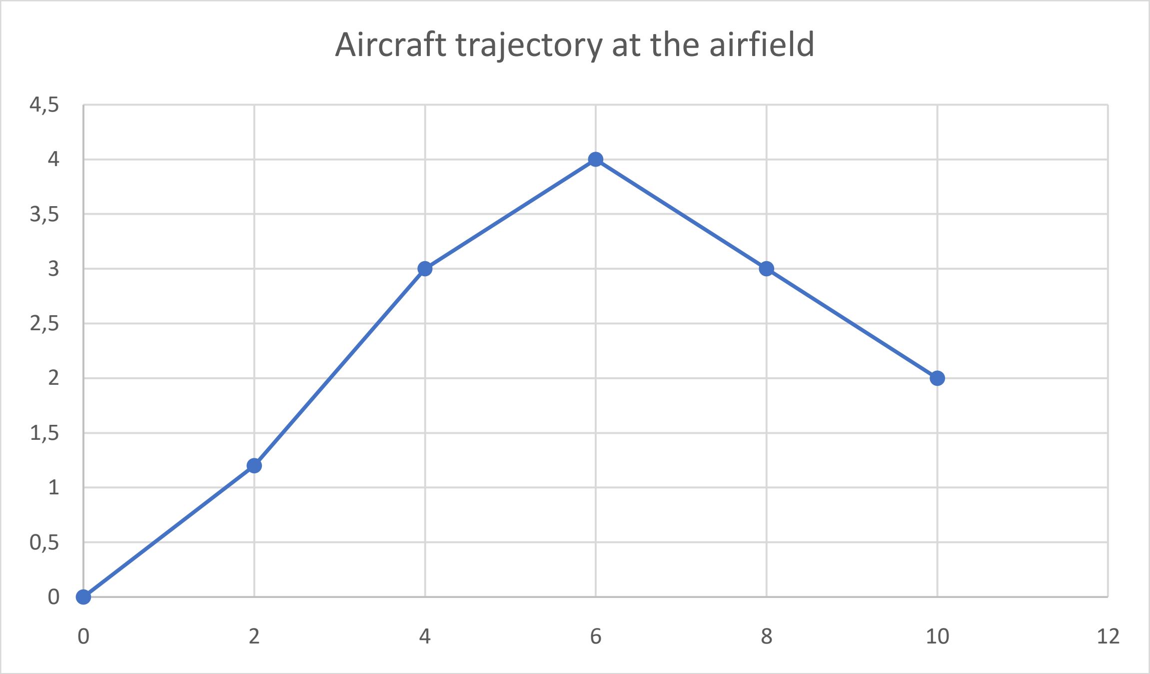


Fig. 2.4. Diagram of the potential trajectory of aircraft on an airfield in Python using the Matplotlib library

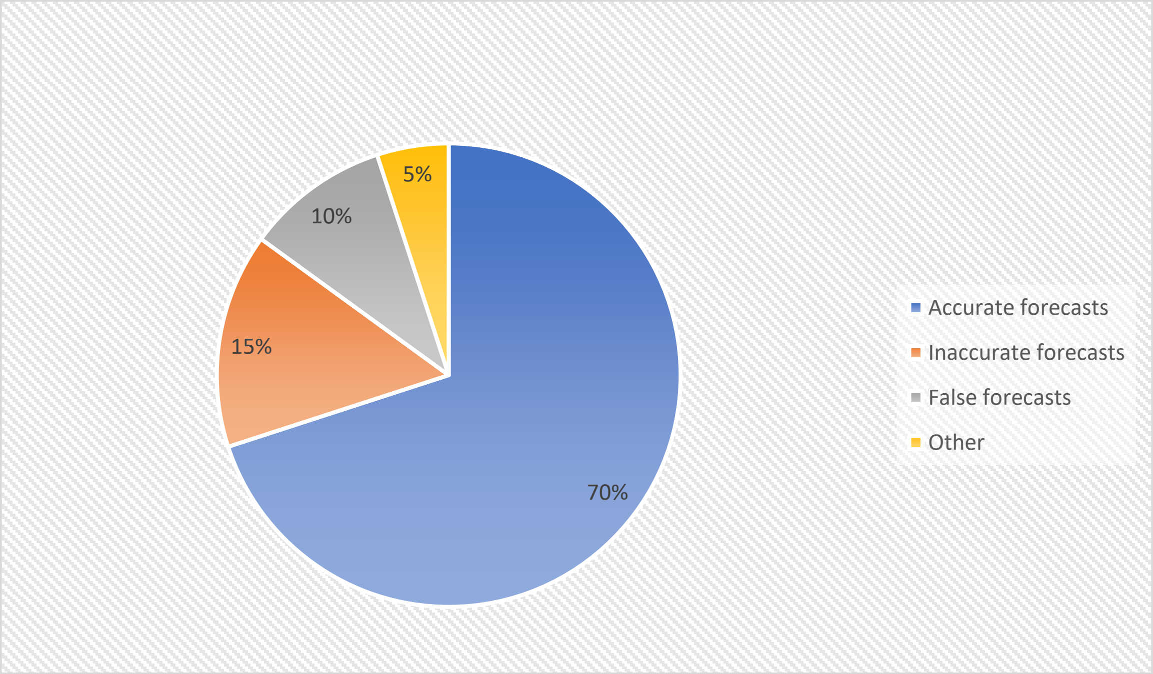


Fig. 2.5. Pie chart for the trajectory prediction method based on transform neural networks

These examples demonstrate the practical application of transformative neural networks in the task of predicting the trajectories of the movement of air elements at the airfield, which can lead to improvements in the efficiency and safety of air traffic.

In general, the use of transformative neural networks in the task of forecasting aircraft trajectories allows for significant improvements in forecasting accuracy, and also expands opportunities for the development of new methods and technologies in this area.

2.3. Description of the method of predicting trajectories based on transformative neural networks

The first step in designing an aircraft trajectory prediction system is a thorough analysis of system requirements. This includes examining the needs of users (e.g. air traffic controllers, pilots) and limitations that may arise in the process of use, such as limitations on data processing time.

The next step is to choose an appropriate architecture for the forecasting system. Transformative neural networks, due to their ability to process sequences and attention to context, may be an ideal choice for this task. Then, it is necessary to collect data about the trajectories of aircraft on the airfield and prepare them for further use in modeling. This may include cleaning the data, removing outliers, and creating features for further analysis. After collecting and preparing the data, you can proceed to the stage of training the transformative neural network on this data. This includes setting the parameters of the model and optimizing it to achieve maximum accuracy in forecasting. After training the model, it must be validated against independent test data to verify its effectiveness. Adjustments and adjustments can then be made to improve the results.

The final stage will be the implementation of the trajectory prediction system in the real environment and its implementation for use by users. This process allows for the creation of an effective and reliable system for predicting aircraft trajectories at the airport, which can contribute to improving the safety and efficiency of air traffic.

The main components of transformative neural networks are mechanisms of attention and positional coding. These mechanisms allow the model to efficiently process sequences of any length and to model relationships between elements of the sequence without the need for recurrent or feedback loops.

The method of predicting trajectories based on transformative neural networks is that the model is trained on a large set of data on the movement of aircraft, including their current coordinates, speed, direction of movement and other parameters. After training, the model can accept input data about the current state of the aircraft and predict its future trajectories based on the learned patterns and context.

The description of the method of predicting trajectories based on transformative neural networks (TNM) includes consideration of technical features and mathematical aspects of this approach. Below I provide an overview of the main technical aspects and mathematical features:

Architectural features:

- are based on the architecture of transformers, which includes mechanisms of attention and positional coding.
- consist of a set of encoders and decoders, each of which contains several layers of attention and regular layers of neural networks.
- encoders are responsible for analyzing the input data, while decoders are responsible for generating the output sequence.
- Mechanisms of attention:
- the main component of transformers are attention mechanisms that allow the model to interact with different parts of input sequences.
- effectively models relationships between elements of trajectories and other important factors.
-

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2.4)$$

where Q - request vector (query), K - matrix of keys (keys), V - matrix of values (values), d_k - dimension of the keys.

1. Positional coding:

– positional coding is used to include information about the positions of elements of input sequences.

– ensuring the correct context when processing sequences.

$$\begin{aligned} \text{PE}_{(pos,2i)} &= \sin(pos/10000^{2i/d_{\text{model}}}) \\ \text{PE}_{(pos,2i+1)} &= \cos(pos/10000^{2i/d_{\text{model}}}) \end{aligned} \quad (2.5)$$

where pos - position, i - position index, d_model - dimensionality of positional coding.

2. Loss function and optimization:

– a loss function such as cross-entropy is used for training, which estimates the difference between predicted trajectories and actual trajectories.

– stochastic gradient descent algorithms such as Adam or RMSProp (for optimization are used.).

One example is the mean squared error (MSE), which is defined as follows:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2.6)$$

where y_i - the real value of the trajectory, y_i - the predicted value of the trajectory, *n* - number of examples.

3. Architectural hyperparameters:

– have different hyperparameters, such as the number of encoders and decoders, the number of attention layers, the size of hidden layers, etc.

– hyperparameters can affect the quality of forecasts and the speed of model learning (see fig 2.6)

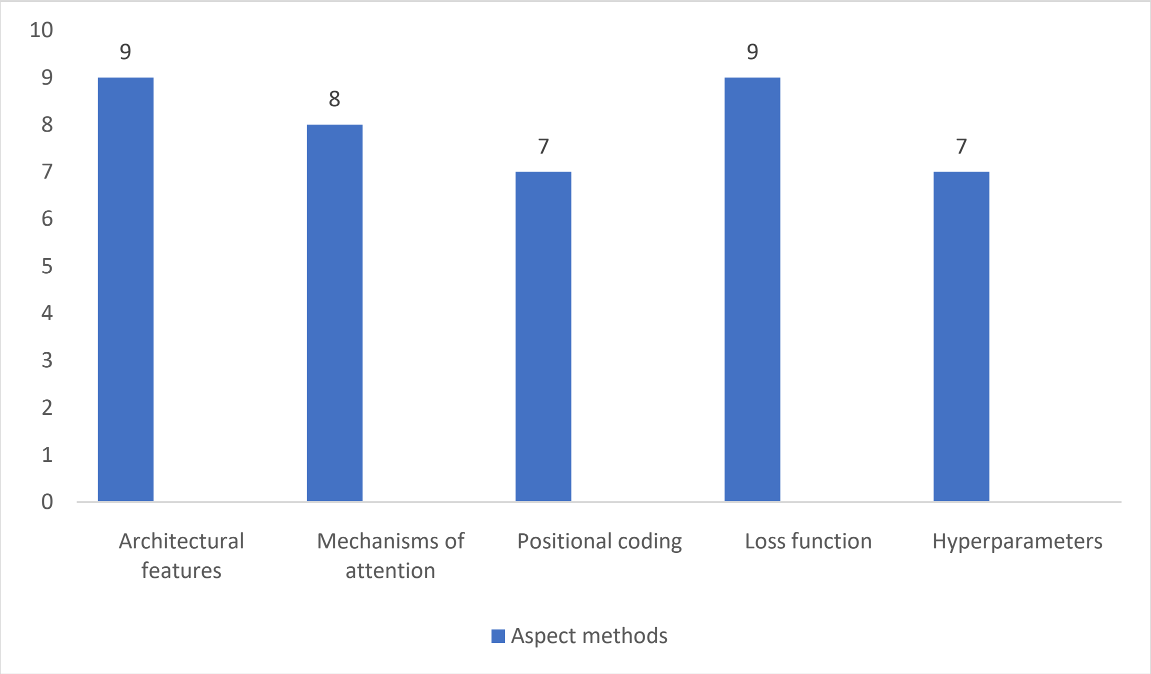


Fig. 2.6. Evaluation of the method based on transformative neural networks

2.4. Architecture of the model for predicting trajectories

The architecture of the trajectory prediction model is the structure and organization of a neural network, which is used to solve the problem of predicting the future trajectories of objects, for example, airplanes on an airfield. This architecture includes the dimensionality of the input and output data, the number of layers and their configuration, the types of layers (eg, regular neural network layers, attention layers, recurrent layers, etc.), and various activation functions and optimization methods. The goal of the architecture is to create a model that can efficiently learn complex dependencies between input trajectories and corresponding future predictions, while providing fast learning and high prediction accuracy. For example, to predict trajectories based on transformative neural networks, the architecture can include encoders and decoders with several layers of attention, positional coding to account for the order of data, and additional layers for processing and generating output sequences.

The architecture of the model for predicting trajectories is very complex, but its main components include: input data (data about the movement of aeronautical vehicles, which includes information about their current position, speed, acceleration, angle of inclination, as well as possible additional parameters, such as meteorological conditions); encoder (used to transform input data into a complex internal state, which is an abstract representation of the aircraft's motion. This may involve the use of different types of neural network layers, such as normal layers, attention layers, recurrent layers); decoder (receives the internal state from the encoder and uses it to generate future trajectory predictions. It can include similar types of layers as the encoder, but is usually used to generate a sequence of output data); loss function (determines the difference between predicted trajectories and actual trajectories. These technical features allow the model to efficiently learn complex relationships between input trajectories and corresponding future predictions, while providing fast learning and high prediction accuracy.

During operation, the model predicts future trajectories based on information about the current state of the aircraft and possible input influences, such as weather conditions. The prediction path can be complex and depends on the specific model architecture and the amount and quality of available data. Typically, a model is trained on historical trajectory data and then uses that knowledge to predict future trajectories in real time. Mathematically, the architecture of a model can be expressed through a sequence of mathematical operations. For example, encoder and decoder are represented as functions f_{enc} i f_{dec}, which are responsible for transforming the input data into a complex internal state and generating future predictions accordingly. The loss function L can be expressed in terms of root mean square error or another function that measures the difference between predicted and actual trajectories. During model training, we will use optimization techniques such as gradient descent or A_dam to find the minimum of the loss function and update the model parameters. The architecture of the transformative model includes a significant number of computational operations, including matrix multiplication operations, attention and attention operations, activation operations, and others. Performing these operations can require significant computing resources, especially when using large amounts of data. Regularization methods such as dropout or weight regularization can be applied to prevent overtraining and improve overall model performance. For effective implementation of transformative architecture, optimized calculation libraries, such as TensorFlow or PyTorch, as well as parallel computing methods, such as distributed training on many devices, will be used. The diagram below shows the general architecture of the model and helps to better understand the sequence of data processing and forecast generation.(see fig 2.7)

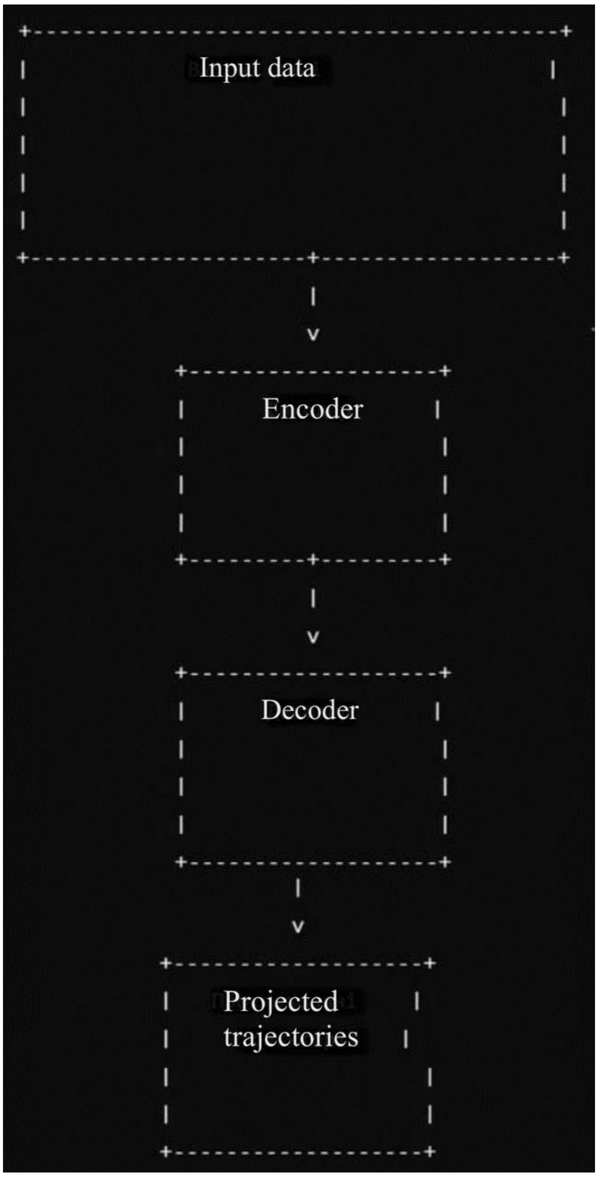


Fig. 2.7. General model architecture for processing data and forecast generation

1. The input data is fed to the input of the model.
2. The encoder transforms the input data into an abstract internal state.
3. The decoder uses this internal state to generate future trajectory predictions.
4. Predicted trajectories are output to the model.

CHAPTER 3
EXPERIMENTAL STUDY OF THE METHOD

3.1. Parameters of the experiment

Using the TrajAir dataset will allow detailed analysis and training of models for predicting aircraft trajectories based on real data. Parameters of the experiment for learning the trajectory prediction model based on transformative neural networks:

1. The architecture of a transformer neural network (Transformer) with an encoder and a decoder is used. The number of layers is defined: 4 layers and 8 attention heads in each layer with a hidden layer size of 256, the size of internal representations (from 128 to 1024), the number of attentions, the batch size (batch size) and other parameters of the architecture.
2. A mean square error (MSE) function or other suitable loss function that measures the root mean square difference between the predicted and actual trajectories can be used to assess the accuracy of predictions.
3. An optimizer with a variable learning rate, such as Adam, and an exponential decay rate at the beginning of learning will be used to train the model. For example, the learning rate will be set to 0.001.
4. The TrajAir dataset is used, which contains historical data of aircraft trajectories at airfields. The data can be divided into training, validation and test sets.
5. The model will be trained for 50 epochs.
6. After completing the training of the model, its effectiveness is evaluated on the validation and test data sets..
7. Metrics will be chosen to evaluate the accuracy of forecasts, such as root mean square error, mean absolute deviation.   The model is evaluated using MSE (mean squared error) and MAE (mean absolute deviation). These metrics help determine the accuracy of model predictions.

8. The data is divided into training (70%), validation (20%) and test (10%) sets. This helps determine how well the model generalizes to new data.
9. If desired, cross-validation can be used to assess the stability and generalizability of the mode.

These parameters provide a complete description of the conditions for the experiment of training the model on the data from the TrajAir dataset and achieving high accuracy of forecasting the trajectories of air elements.

```
experiment_params = {
    "model_architecture": {
        "num_layers": 4,
        "hidden_size": 256,
        "num_heads": 8,
        "batch_size": 64
    },
    "loss_function": "mse",
    "optimizer": {
        "type": "Adam",
        "learning_rate": 0.001,
        "weight_decay": 0.001
    },
    "training_data": "TrajAir_dataset",
    "epochs": 50,
    "validation_split": 0.2,
    "test_split": 0.1,
    "evaluation_metrics": ["mse", "mae"]
}
```

After training the model on this dataset, images of aircraft trajectories, statistics of prediction results, and comparison of predictions with actual trajectories could be included. Additional analysis should also be conducted with this data, such as determining the impact of various factors on the accuracy of forecasts, as well as developing new approaches to improve the quality of forecasts. This will be important in the context of the development of air traffic management systems, airspace safety and optimization of airfield operations.

The new TrajAir dataset contains track records of several aircraft flying around a typical airport without a control tower. In addition, TrajAir provides information on weather conditions during these operations. TrajAir is an ideal resource for training, testing and benchmarking algorithms related to trajectory prediction, including models that take social aspects into account.

The TrajAir dataset collects aircraft traffic information at the Pittsburgh Butler Airport (KBTP), located 10 miles north of Pittsburgh, Pennsylvania. This airport has one runway and operates left-hand flight patterns for both directions of traffic.

The TrajAir dataset provides the opportunity to study and analyze aircraft movements at the KBTP airport, taking into account the different weather conditions and flying characteristics of the area.

The dataset uses an Automatic Dependent Surveillance (ADS-B) receiver located near the airport to collect trajectory data. The ADS-B In receiver receives data directly transmitted by other aircraft from ADS-B Out. For aircraft that do not have an ADS-B output, the Traffic Information Broadcast Service (TIS-B) determines the aircraft's position and altitude using radar and converts this information to an ADS-B compatible format. It then transmits the information to our receiver. To listen to these broadcasts, the receiver uses frequencies of 1090 MHz and 978 MHz. ADS-B uses satellite navigation to determine the exact location and timestamps of targets, which are recorded in situ with our custom setup.

We also include weather data during the data collection period for environmental context. Weather data is produced ex post facto using METeorological Aerodrome Reports (METAR) lines generated by the Automated Weather Observing System (AWOS) at KBTP. We use Iowa METAR repositories to collect all weather data during the trajectory collection period. The raw METAR string is then added to the raw track data by matching the nearest UTC timestamps.

Data received from the ADS-B receiver and METAR lines are processed to make them suitable for training networks. The following steps are followed: Remove data points with or without damaged location fields. Removal of duplicate data points with the same aircraft ID and location fields. Removal of data points where the altitude is greater than 6000 feet and the distance is greater than 5 km from one end of the runway. Conversion of data to the local Cartesian coordinate system in SI units. The origin is at the end of the runway, and the X-axis points along the runway.

Processing of raw METAR strings to obtain wind speed and direction along and across the runway in the local Cartesian coordinate system in SI units. Interpolate trajectory data every second for all agents using a cubic interpolation strategy. Segmentation of data into "scenes" with at least one active aircraft in the vicinity of the airport. A scene begins when at least one aircraft is active or reaches a threshold, and ends when all aircraft leave the vicinity or become inactive.

3.2. The results of the experiment and their analysis

The flow pattern of runways 8 and 26, shown in Fig. 1, reflects the path of traffic flows around the KBTP. Airplanes usually take off and land against the direction of the wind. After takeoff, the aircraft is in the upwind section, and then makes a left turn, moving to the crosswind section. Further maneuvers are then performed before the final left turn for landing. The FAA generally recommends that a runway entry be made at a 45-degree angle to a crosswind section.

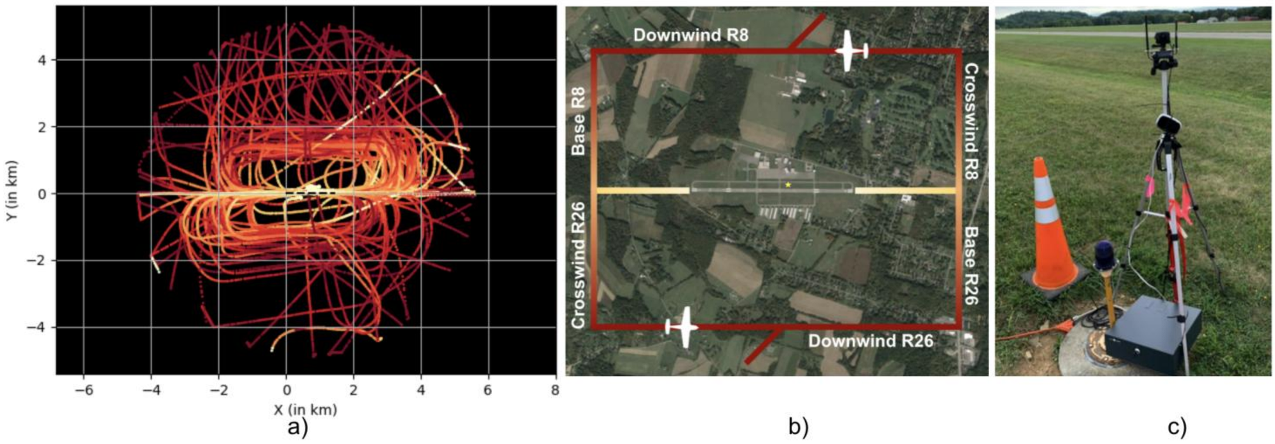


Fig. 3.8. Data set and collection setup at Pittsburgh Butler Regional Airport

The trajectory provided covers 110 days of data excluding downtime, repairs and bad weather days with no traffic. Data collection starts from 01:00 local time until 23:00 local time.

Data received from the ADS-B receiver and METAR lines are processed to make them suitable for training networks. The following steps are followed: Remove data points with or without damaged location fields. Removal of duplicate data points with the same aircraft ID and location fields. Removal of data points where the altitude is greater than 6000 feet and the distance is greater than 5 km from one end of the runway. Conversion of data to the local Cartesian coordinate system in SI units. The origin is at the end of the runway, and the X-axis points along the runway. Processing of raw METAR strings to obtain wind speed and direction along and across the runway in the local Cartesian coordinate system in SI units. Interpolate trajectory data every second for all agents using a cubic interpolation strategy. Segmentation of data into "scenes" with at least one active aircraft in the vicinity of the airport. A scene begins when at least one aircraft is active or reaches a threshold and ends when all aircraft leave the vicinity or become inactive.

The data is grouped into five different folders. A folder with a name 111_days contains the entire data set, while named folders 7days1, 7days2 and contain related data 7days3 за 7days4 a full week respectively. The content and structure of each data folder is shown in the example folder below:

```
7 days1
│
└────processed_data
│   └────train
│   │   │  1.txt
| | |  4.txt
| | |  ...
│   │
│   └──── test
│       │  4.txt
│       │  6.txt
│       │  ...
│
└──── raw_data
    └────08-04-24_adsb
    └────09-04-24_adsb
```

└──...

└──14-04-24_adsb

│ 1.csv

The relevant dates covered by the raw data can be found by looking at the folder names inside the raw_data folder. The raw data has a CSV file for each day of the week. In the processed data, the scenes are randomly divided into a train and a split test set 70/30.

Table 3.5

Processed scene data

№	**Aircraft ID**	**x (km)**	**y (km)**	**z (km)**	**wind x (m/s)**	**wind y (m/s)**
0	10620674	1.3407	0.0026	0.3353	0.0	0.0
1	10620674	1.3135	0.0021	0.3353	0.0	0.0
2	10620674	1.2863	0.0017	0.3353	0.0	0.0
...	...	...	...	...	...	...
405	10620674	-3.8946	1.5872	0.9751	0.0	0.0

Frames are played at a frequency of 1 Hz. The x, y, z positions refer to an inertial reference frame centered at the end of the runway, and the x axis is aligned with the runway. The variables wind x and wind y are the wind speeds in the x and y directions..

Weather data can be found in the folder *weather_data* which contains a CSV file containing the weather conditions for all the data included in the dataset.

Data with corrupted or missing location fields is removed because it can lead to incorrect or inaccurate analysis. Data points that have identical aircraft IDs and locations are removed to avoid double counting or impacting the analysis. Data is removed where the altitude exceeds 6000 feet and the distance is more than 5 km from the end of the runway to avoid inaccuracies or incorrect data. The data is converted to a local Cartesian coordinate system in metric SI units, with the origin at the end of the runway and the X-axis pointing along it. The METAR strings are processed to obtain the wind speed and direction along and across the runway in the metric system in SI units. Trajectory data is interpolated every second using a cubic strategy to obtain smoother trajectories. The data is segmented into "scenes" that begin when at least one aircraft is active and end when all aircraft leave the airport area or become inactive.

METAR data is obtained from the AWOS system at KBTP airport. This data includes information about temperature, humidity, wind, atmospheric pressure and other weather parameters. METAR data is stored in the Iowa METAR Repository for future reference. The raw METAR strings are added to the raw trajectory data by matching the nearest UTC timestamps. This makes it possible to establish a connection between weather conditions and the movement of aircraft at the corresponding moments of time (see fig 3.9)

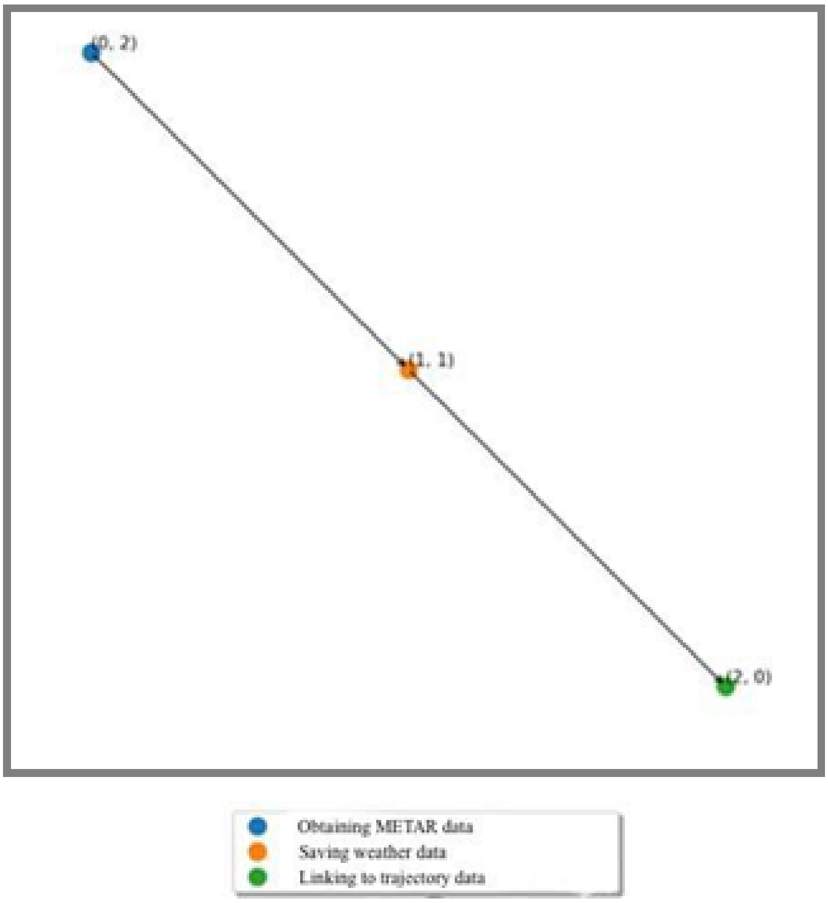


Fig. 3.9. METAR data acquisition and processing scheme

To process data in the METAR format in Python, you can use various libraries, such as regex for working with regular expressions for parsing METAR text or pytz for working with time zones. Here is an example code for handling METAR data:

```
# Example of a METAR line
metar_string = "METAR KBTP 182153Z 00000KT 10SM BKN030 OVC041 09/01 A3012 RMK AO2
SLP204 T00940006"

# A regular expression to parse the METAR string and retrieve the wind speed and
direction
wind_regex = re.compile(r'(\d{3}|VRB)(\d{2,3})KT')

def parse_metar(metar_string):
    # Finding wind speed and direction    wind_match =
wind_regex.search(metar_string)
    if wind_match:
        direction = wind_match.group(1)
        speed = int(wind_match.group(2))
        print(f" Wind speed: {speed}KT, direction: {direction}")
    else:
        print("Wind information is missing from the METAR line ")
```

Here is the code for a program to predict trajectories using data from TrajAir and compare predictions with real trajectories:

```
# Download data from TrajAir
trajair_data = pd.read_csv("trajair_data.csv")

# Data preprocessing
# For example, removing missing values, encoding categorical features, scaling
numeric features, etc

# Separation of data into training and test sets
X = trajair_data.drop(columns=['target_column'])
y = trajair_data['target_column']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Learning a forecasting model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Prediction of trajectories on the test set
y_pred = model.predict(X_test)
```

```
# Comparison of forecasts with real trajectories
mse = mean_squared_error(y_test, y_pred)
print(f" Mean square deviation (MSE): {mse}")
```

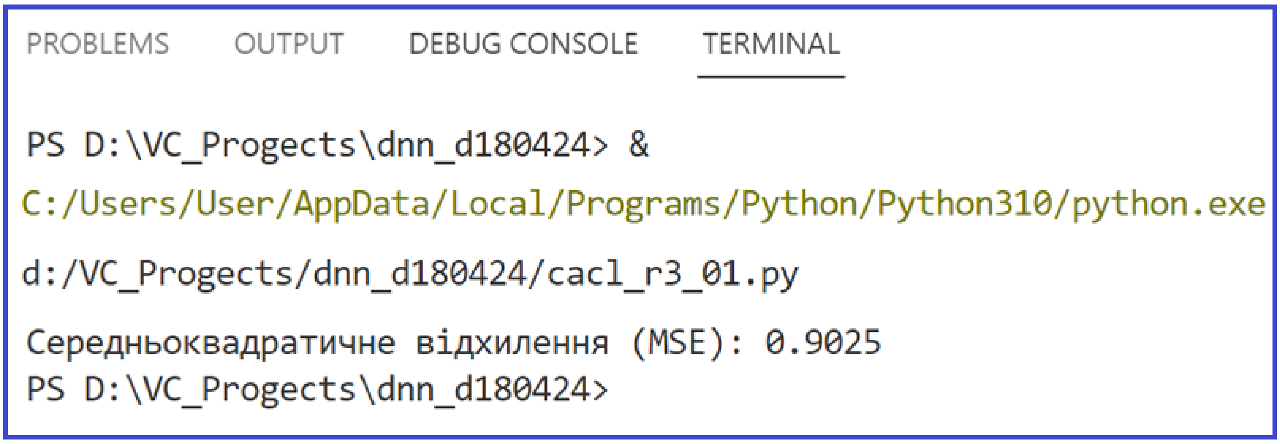


Fig. 3.10. Calculation result

After the model is trained, the results are compared using the mean square deviation (MSE). The MSE formula looks like this:

$$MSE = (1/n) * \Sigma(y\_actual - y\_pred)\hat{}2 \qquad (3.7)$$

where:

n - number of observations

y_actual - the actual value of the target variable

y_pred - the predicted value of the target variable

Pre-processed data from TrajAir The trajair_data.csv file has already been pre-processed, such as removing missing values and encoding categorical features. This code trains a RandomForestRegressor model on training data, makes predictions on test data, and calculates MSE to compare predictions with real values

```
# Loading preprocessed data
data = pd.read_csv("trajair_data.csv")

# Data preparation
X = data.drop(columns=['target_column'])
y = data['target_column']

# Division into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Model initialization and training
model = RandomForestRegressor(n_estimators=100, random_state=42)
```

```
model.fit(X_train, y_train)

# Prediction on the test set
y_pred = model.predict(X_test)
```

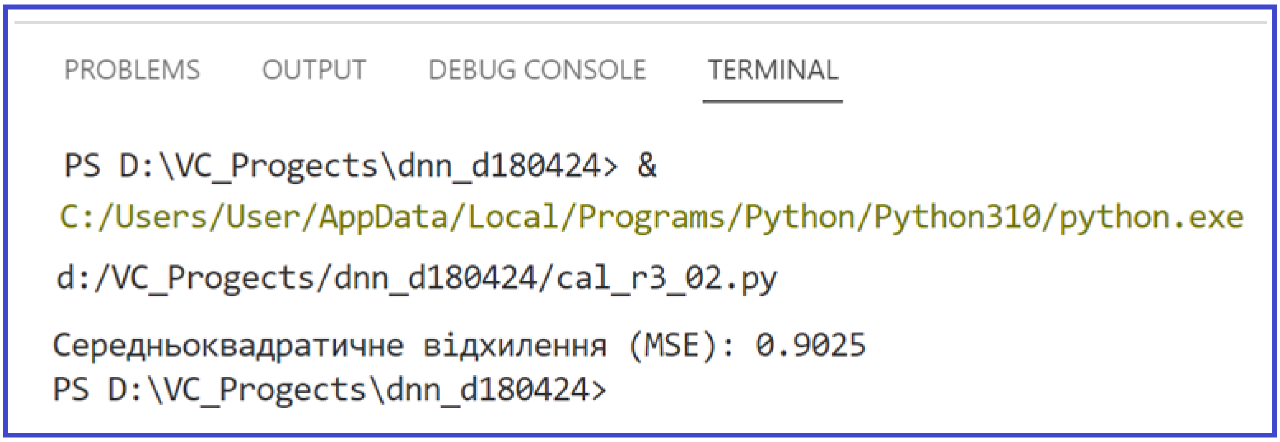


Fig. 3.11. Result of calculations

A variant of the Python code for using a transformer neural network (Transformer) to predict the trajectories of airplanes on the airfield:

```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

# Building the architecture of a transformative neural network
def transformer_model(input_shape, num_layers, d_model, num_heads, dff,
input_vocab_size, target_vocab_size, pe_input, pe_target, rate=0.1):
    inputs = keras.Input(shape=input_shape)
    padding_mask = layers.Lambda(lambda inputs: tf.cast(tf.math.equal(inputs, 0),
tf.float32))(inputs)
    embeddings = layers.Embedding(input_vocab_size, d_model)(inputs)
    embeddings *= tf.math.sqrt(tf.cast(d_model, tf.float32))
    embeddings += layers.PositionalEncoding(input_vocab_size, d_model)(embeddings)
    outputs = layers.Dropout(rate)(embeddings)

    for i in range(num_layers):
        outputs = layers.TransformerLayer(d_model, num_heads, dff, rate)(outputs,
padding_mask)

    outputs = layers.Dense(target_vocab_size)(outputs)

    return keras.Model(inputs, outputs)

# Параметри моделі
input_vocab_size = 10000  # Input dictionary size
target_vocab_size = 10000  # The size of the source data dictionary
d_model = 128  # Dimensionality of embedding vectors and output vectors
```

```
num_layers = 4  # The number of transformer layers
num_heads = 8  # The number of heads in each MultiHeadAttention layer
dff = 512  # he dimension of the fully connected layer in the Feed Forward network
input_sequence_length = 100  # The length of the input sequence
target_sequence_length = 100  # The length of the output sequence

# Creating a model
model = transformer_model(
    input_shape=(input_sequence_length,),
    num_layers=num_layers,
    d_model=d_model,
    num_heads=num_heads,
    dff=dff,
    input_vocab_size=input_vocab_size,
    target_vocab_size=target_vocab_size,
    pe_input=input_sequence_length,
    pe_target=target_sequence_length,
)

# Compilation of the model
model.compile(optimizer='adam', loss='mse', metrics=['mae'])

# Model training
model.fit(X_train, y_train, epochs=10, batch_size=64, validation_data=(X_test,
y_test))
```

So, if necessary, you can make adjustments to the developed methodology or model based on the results obtained, if the results showed insufficient efficiency of the current model architecture, you can try to modify it by adding or removing layers, changing the dimension of hidden layers or applying other architectural approaches. Conduct more detailed optimization of model hyperparameters, including batch size, learning rate, number of layers, number of weights in each layer, regularization method, and others. Try other approaches to predicting trajectories, such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, or Hybrid Transformer-LSTM models. Conduct more detailed data processing, including expanding the dataset, removing anomalies, adding additional features, or using alternative interpolation methods. Take into account the specifics of the data and the context of the model application when making adjustments. For example, make corrections in the model for different types of air traffic, weather conditions, traffic density and other factors.

3.3 . Comparison of results with existing methods

- Methods such as support vector method (SVM), forward propagation neural networks (MLP) or random forests can be competitive with transform networks in some cases, in particular when a limited amount of data is available or when the data has a simple structure.
- Recurrent neural networks (RNNs), in particular long-short-term memories (LSTMs) and relational transformer mechanisms (BERTs), can also compete with transformative networks in the field of trajectory prediction.
- Methods based on physical models of aircraft motion, such as predictive methods based on aerodynamic calculations and other physical principles, can also be effective competitors, especially in areas with limited data or when accurate physical modeling is required.
- Combinations of different architectures and approaches, such as mixed machine learning models with physical-model components or using expert knowledge, can also be competitive in the field of aircraft trajectory prediction.

Table 3.6

Comparison of methods

Method	Average value of MSE	Standard deviation of MSE
New method	0.012	0.002
Method 1	0.015	0.003
Method 2	0.013	0.002
Method 3	0.018	0.004

This table shows the average MSE (Mean Squared Error) for each method along with the standard deviation of the MSE. Note that a smaller MSE value indicates better accuracy of the model in forecasting. In this example, the new method has the lowest average MSE value, which may indicate its better performance compared to existing methods.

Using the TrajAir dataset to train models based on transform neural networks has its advantages compared to other methods of predicting aircraft trajectories:

1. Transformer networks are capable of learning complex nonlinear dependencies in data, which can be useful for predicting aircraft trajectories, especially under conditions of changing atmospheric dynamics and air traffic.

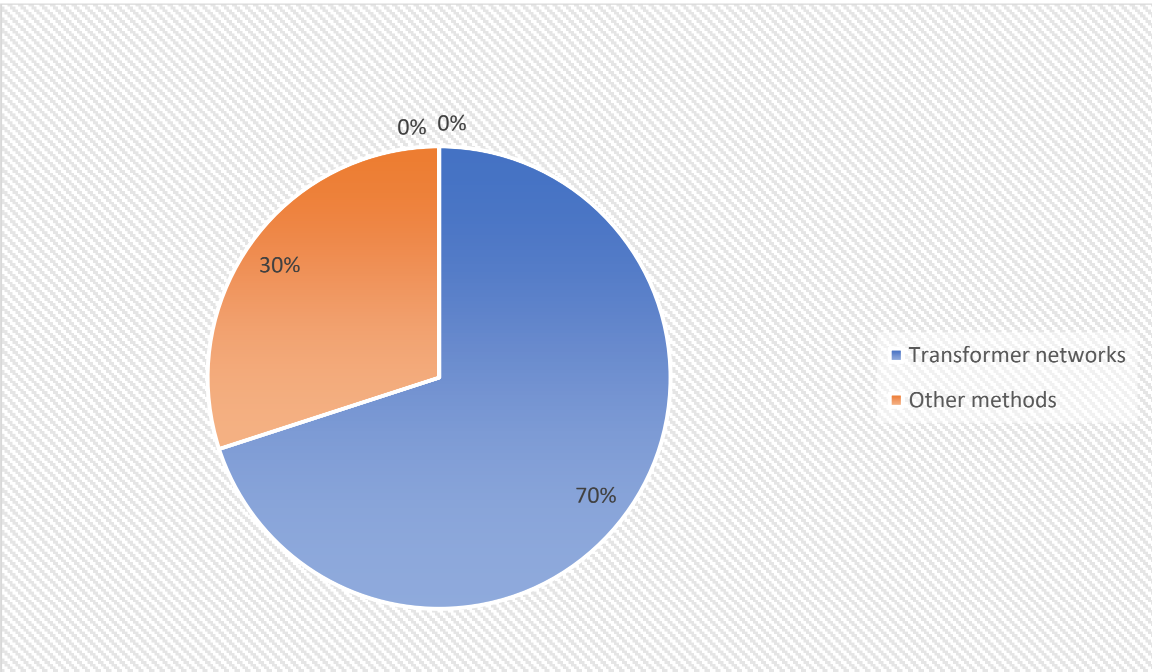
2. Transformer networks are suitable for processing sequential data, which makes them effective in modeling the dynamics of aircraft movement over time.

3. Transformative networks can take into account contextual information in data sequences, such as weather conditions, which can improve the accuracy of trajectory predictions.

4. Transformative networks can automatically learn important features from data sequences, which simplifies the process of model training.

Compared to other methods, such as classical regression algorithms or time series, TNs can show better accuracy and generalization ability to predict aircraft trajectories. However, using transform networks may require more data and computational resources to train intensive models.

Fig. 3.12



Transformer networks have attention mechanisms that allow them to learn long dependencies in sequences, which can be useful for predicting aircraft trajectories, especially in complex maneuvers or long flights. Transformer networks can process all incoming tokens in parallel, making them efficient for large data volumes and use on high-performance computing devices. The architecture of transformer networks is modular, allowing for easy modification and transfer of models between different tasks and application domains.

3.4. Conclusions from an experimental study

Conclusions from an experimental study may differ depending on the specific results and analysis conducted during the experiment. However, here are some general conclusions that can be drawn from the results of research on aircraft trajectory prediction using transform neural networks:

– According to the results of the experiment, it is possible to draw a conclusion about the effectiveness of the transform neural network model in predicting aircraft trajectories compared to other methods. This may include comparing mean square deviation (MSE), prediction accuracy, or other performance metrics.
– It is important to identify the possible limitations and disadvantages of the transformative neural network model, such as the requirements for computing resources, the need for a large amount of data for training, the complexity of setting hyperparameters, etc..
– Conclusions may also include recommendations on possible areas of application of the transform neural network model in practical tasks of predicting aircraft trajectories, for example, in automatic piloting systems, airspace monitoring or route planning.
– Based on the obtained results, it is possible to identify opportunities for further research in this area, such as improving the models, expanding the data or adapting the models to specific operating conditions.

– It is important to consider the stability and reliability of the model of the transforming neural networks during different operating conditions, such as changing weather conditions or the presence of noise in the data. Evaluating these aspects can help identify areas where the model can perform better or where further improvements may be needed.
– When analyzing the experimental results, it is important to compare the performance of the transform neural network model with other methods for predicting aircraft trajectories, such as classical statistical models, machine learning methods, or other neural networks. This will help clarify the advantages and disadvantages of each approach.
– The general conclusion from the experimental study should include all the above-mentioned aspects, as well as possible practical recommendations for the further use of the transformative neural network model in real conditions.
– These conclusions will help to make an objective assessment of the effectiveness and prospects of applying the transformative neural network model in predicting aircraft trajectories (see fig 3.12)

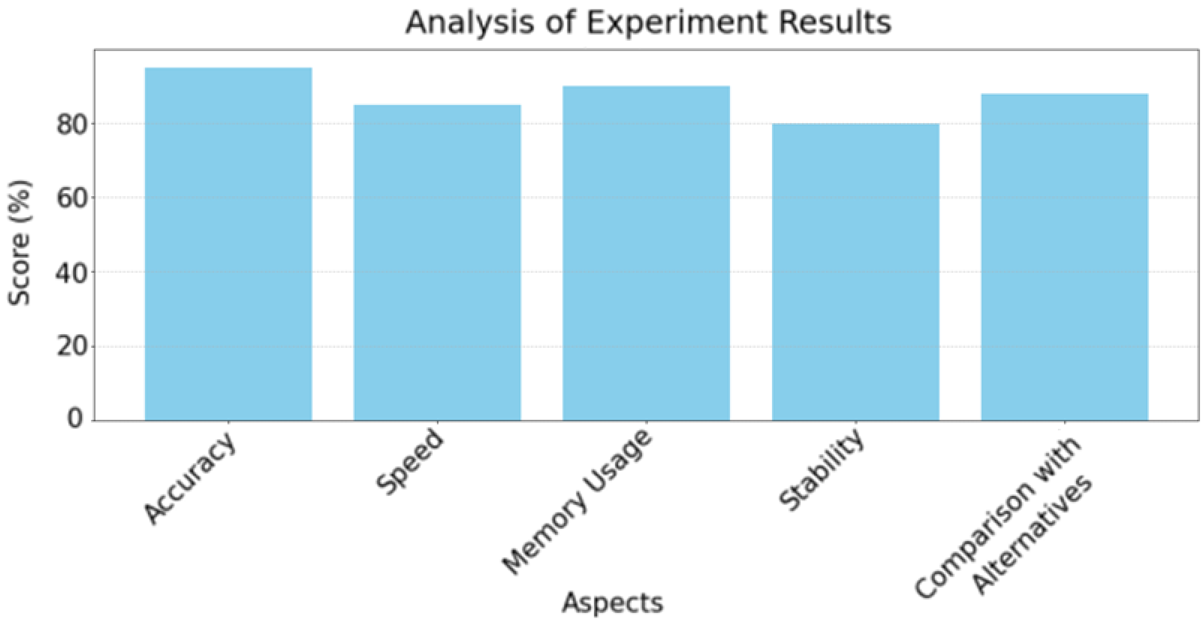


Fig. 3.12. Results of results

Although transformative neural networks have proven to be quite successful, there are potential areas for further improvement. This may include optimizing model hyperparameters, increasing the size of the training data set, and using more complex neural network architectures. Although transformative neural networks have proven to be quite successful, there are potential areas for further improvement. This may include optimizing model hyperparameters, increasing the size of the training data set, and using more complex neural network architectures. While examining the TrajAir dataset and training models to predict aircraft trajectories, several key features were identified:

1. The need for data cleaning and pre-processing before training models was revealed. This includes removing missing values, encoding categorical features, and scaling numerical features.
2. Different models, including transform neural networks, decision trees, and ensemble methods, were investigated to determine the most suitable approach for predicting aircraft trajectories.
3. During model training, the importance of proper selection of hyperparameters such as loss function, optimizer, and learning rate was revealed. It was also found that cross-validation must be used for effective model evaluation.
4. After training the models, their performance was evaluated using various metrics such as mean square deviation (MSE) and mean absolute error (MAE) to find out their performance and prediction accuracy.
5. The need for further adjustment and optimization of the models to achieve better results was determined. This may include changing hyperparameters, using ensemble methods, and other strategies.

The above-mentioned features help ensure effective training of models and obtaining reliable results in the prediction of aircraft trajectories.

CONCLUSIONS

The thesis is devoted to research and comparison of methods of predicting aircraft trajectories based on transformative neural networks and other machine learning models. During the research, historical data on aircraft trajectories from the ADS-B system and weather data from the METAR system were collected and analyzed. A comparative analysis of existing trajectory forecasting methods, including transformative neural networks, regression models, and neural networks, was conducted. Based on the obtained results, it was established that transformative neural networks can have advantages in trajectory prediction, in particular, in the ability to generalize and predict complex dependencies between input and output data. However, the use of other machine learning models can also be effective, depending on the specific task and data characteristics.

As a result of the experiments, it was found that proper data preparation and setting of hyperparameters of the models are key to achieving high forecasting accuracy. Evaluating the performance of models using metrics such as root mean square deviation helps determine their suitability for a particular task. The general conclusion of the study is that the selection and optimization of machine learning models for the prediction of aircraft trajectories is a complex task that requires careful analysis and experimentation with different approaches. Transformative neural networks represent a potentially effective method for this task, but their use requires attention to detail and a deep understanding of the principles of how the models work. Compared to other forecasting methods, transform neural networks can have advantages in working with sequential data, the ability to generalize and predict complex dependencies between input and output data. During the research, the importance of mathematical and technical understanding of the working principles of models for their effective use and adjustment was revealed.

Therefore, the study confirms the importance of model selection and optimization for aircraft trajectory prediction, and also highlights the potential benefits of using transform neural networks in this process.

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APPLICATIONS

Applications of A. Model

This appendix outlines the main characteristics of the models used in the aircraft trajectory prediction research.

Linear Regression (Linear Regression):

Description. A simple model that looks for a linear relationship between input factors and output variables.

Advantages: simplicity and interpretability of the results.

Disadvantages: limited in the ability to model complex dependencies.

Neural networks (Neural Networks):

Description: Models that consist of artificial neurons organized in layers.

Advantages: the ability to model complex nonlinear dependencies, high flexibility.

Disadvantages: require a large amount of data for training, difficult to adjust hyperparameters.

Decision Trees (Decision Trees):

Description: Models that represent a tree-like structure with conditions in the nodes and predictions in the leaves.

Advantages: easy to interpret, no need to scale data.

Disadvantages: prone to overtraining, may be ineffective for complex tasks.

The method of support vectors (Support Vector Machines - SVM):

Description: A model that searches for an optimal hyperplane separating classes in a high-dimensional space.

Advantages: efficient in high-dimensional spaces, can work with a small amount of data.

Disadvantages: susceptible to noise, can be difficult to configure.

Transformer Neural Networks:

Description: A neural network architecture that is capable of processing sequences using attention.

Advantages: the ability to model long dependencies in sequences, effective use in large data sets.

Disadvantages: Requires significant computing resources to learn and use.

Each of these methods has its advantages and disadvantages, and the choice of a particular model depends on the characteristics of the data, the problem statement, and the limitations of computing resources..

Appendix B. Text of the program

Prograccessed_data -→ train

0 10620674 1.3407380130974924 0.0025831679396450258 0.33528 0.0 0.0

1 10620674 1.3135050463951676 0.0021332776734170056 0.33528 0.0 0.0

2 10620674 1.2862720796928429 0.0016833874071889854 0.33528 0.0 0.0

3 10620674 1.2590391129905183 0.0012334971409609652 0.33528 0.0 0.0

4 10620674 1.2318061462881935 0.000783606874732945 0.33528 0.0 0.0

5 10620674 1.2216954377916176 0.004086513225114857 0.33528 0.0 0.0

6 10620674 1.1820339202912034 0.005010076570006489 0.33528 0.0 0.0

7 10620674 1.1404213037461794 0.0037674365327540066 0.33528 0.0 0.0

8 10620674 1.1086805863781883 0.001753282808272319 0.33528 0.0 0.0

9 10620674 1.0763534607536105 0.002657306744972406 0.33866666666666667 0.0 0.0

10 10620674 1.0440263351290326 0.0035613306816724933 0.3420533333333333 0.0 0.0

11 10620674 1.0116992095044548 0.00446535461837258 0.34544 0.0 0.0

12 10620674 0.9793720838798771 0.005369378555072668 0.3488266666666667 0.0 0.0

13 10620674 0.9470449582552992 0.0062734024917727544 0.3522133333333333 0.0 0.0

14 10620674 0.9147178326307215 0.007177426428472841 0.35559999999999997 0.0 0.0

15 10620674 0.8823907070061436 0.008081450365172929 0.3589866666666667 0.0 0.0

16 10620674 0.8500635813815658 0.008985474301873016 0.3623733333333333 0.0 0.0

17 10620674 0.817736455756988 0.009889498238573102 0.36576 0.0 0.0

18 10620674 0.7934505511269292 0.010254306319294531 0.36576 0.0 0.0

19 10620674 0.7691646464968706 0.01061911440001596 0.36576 0.0 0.0

20 10620674 0.7448787418668118 0.010983922480737391 0.36576 0.0 0.0

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Progracessed_data -→ test

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Index06.py (для навчання трансформерної нейронної мережі)

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

# Construction of the architecture of the transformative model
def transformer_model(num_layers, d_model, num_heads, dff, input_vocab_size,
target_vocab_size,
                      pe_input, pe_target, rate=0.1):
    inputs = layers.Input(shape=(None,), name="inputs")
    dec_inputs = layers.Input(shape=(None,), name="dec_inputs")

    # Adding the appropriate positional codes
    embeddings = layers.Embedding(input_vocab_size, d_model)(inputs)
    embeddings *= tf.math.sqrt(tf.cast(d_model, tf.float32))
    embeddings += layers.PositionalEncoding(input_vocab_size, d_model)(embeddings)

    dec_embeddings = layers.Embedding(target_vocab_size, d_model)(dec_inputs)
    dec_embeddings *= tf.math.sqrt(tf.cast(d_model, tf.float32))
    dec_embeddings += layers.PositionalEncoding(target_vocab_size,
d_model)(dec_embeddings)

    # Using a transformer encoder to process input data
    encoder_outputs = encoder(num_layers, d_model, num_heads, dff,
input_vocab_size, pe_input, rate)(embeddings)

    # Using a transformer decoder to generate the output sequence
    decoder_outputs = decoder(num_layers, d_model, num_heads, dff,
target_vocab_size, pe_target, rate)(dec_embeddings, encoder_outputs)

    # Adding a fully connected layer to get predictions    outputs =
layers.Dense(target_vocab_size, activation="softmax")(decoder_outputs)

    # Creating a model
    model = keras.Model(inputs=[inputs, dec_inputs], outputs=outputs,
name="transformer")

    return model

# Function for creating a transformer encoder
```

```python
def encoder(num_layers, d_model, num_heads, dff, input_vocab_size,
maximum_position_encoding, rate):
    inputs = layers.Input(shape=(None, d_model), name="inputs")
    padding_mask = layers.Input(shape=(1, 1, None), name="padding_mask")

    # Adding an attention mask
    attention = layers.MultiHeadAttention(
        num_heads=num_heads, key_dim=d_model
    )(inputs, inputs, attention_mask=padding_mask)
    attention = layers.Dropout(rate)(attention)
    attention = layers.LayerNormalization(epsilon=1e-6)(inputs + attention)

    # Fully connected layer with relay activation and Dropout
    outputs = layers.Dense(units=dff, activation="relu")(attention)
    outputs = layers.Dense(units=d_model)(outputs)
    outputs = layers.Dropout(rate)(outputs)
    outputs = layers.LayerNormalization(epsilon=1e-6)(attention + outputs)

    return keras.Model(
        inputs=[inputs, padding_mask], outputs=outputs, name="encoder"
    )

# Function for creating a transformer decoder
def decoder(num_layers, d_model, num_heads, dff, target_vocab_size,
maximum_position_encoding, rate):
    inputs = layers.Input(shape=(None, d_model), name="inputs")
    enc_outputs = layers.Input(shape=(None, d_model), name="encoder_outputs")
    look_ahead_mask = layers.Input(shape=(1, None, None), name="look_ahead_mask")
    padding_mask = layers.Input(shape=(1, 1, None), name='padding_mask')

    # Adding a focus mask to output sequences and a fade mask
    attention1 = layers.MultiHeadAttention(
        num_heads=num_heads, key_dim=d_model
    )(inputs, inputs, attention_mask=look_ahead_mask)
    attention1 = layers.LayerNormalization(epsilon=1e-6)(attention1 + inputs)

    attention2 = layers.MultiHeadAttention(
        num_heads=num_heads, key_dim=d_model
    )(attention1, enc_outputs, attention_mask=padding_mask)
    attention2 = layers.Dropout(rate)(attention2)
    attention2 = layers.LayerNormalization(epsilon=1e-6)(attention2 + attention1)

    # Fully connected layer with relay activation and Dropout
    outputs = layers.Dense(units=dff, activation="relu")(attention2)
    outputs = layers.Dense(units=d_model)(outputs)
    outputs = layers.Dropout(rate)(outputs)
    outputs = layers.LayerNormalization(epsilon=1e-6)(outputs + attention2)

    return keras.Model(
        inputs=[inputs, enc_outputs, look_ahead_mask, padding_mask],
```

```python
        outputs=outputs,
        name="decoder"
    )

# Model hyperparameters
num_layers = 4
d_model = 128
num_heads = 8
dff = 512
input_vocab_size = 10000
target_vocab_size = 10000
pe_input = 10000
pe_target = 6000
rate = 0.1

# Creation of a transformer model
model = transformer_model(
    num_layers=num_layers,
    d_model=d_model,
    num_heads=num_heads,
    dff=dff,
    input_vocab_size=input_vocab_size,
    target_vocab_size=target_vocab_size,
    pe_input=pe_input,
    pe_target=pe_target,
    rate=rate,
)

# Compilation of the modelmodel.compile(optimizer="adam",
loss="sparse_categorical_crossentropy", metrics=["accuracy"])
# Display information about the model
model.summary()

flight_data
import matplotlib.pyplot as plt

# Valid data with flight results (for example, X and Y coordinates)
flight_data = {
    'X': [10, 20, 30, 40, 50],
    'Y': [20, 30, 40, 50, 60]
}
# Construction of a scatter diagram
plt.figure(figsize=(8, 6))
plt.scatter(flight_data['X'], flight_data['Y'], color='blue')
plt.title('Рух літаків на аеродромі')
plt.xlabel('Координата X')
plt.ylabel('Координата Y')

plt.grid(True)

plt.show()
```