Artificial Intelligence Applications in Road Traffic Forecasting: A Review of Current Research

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***Abstract* - Artificial intelligence (AI) is revolutionizing data processing and analysis due to its exceptional capability to detect and forecast future trends. This makes it an obvious alternative to traditional methods of traffic demand forecast, which is the core element of transportation planning. While AI real-time and short-term traffic forecasts application has been widely investigated, long-term applications are notably limited. This paper examines the current state of AI in traffic forecasting, outlining both its challenges and opportunities. Most AI applications in traffic forecasting related research focus on single-point analysis methods, lacking a broader spatio-temporal context. To fully leverage AI's capabilities, it's important to address the gap in understanding how spatial attributes affect traffic behaviour. While the choice of input variables, analysis methods, and model structures significantly impacts the effectiveness of traffic forecasts, data validation is another crucial aspect of the effective application of AI methods. Knowledge-based systems are effective for data analysis, modelling, and multi-criteria decision-making. Neural networks are increasingly vital for traffic control and route guidance. Two AI techniques have shown promise in traffic forecasting: Back Propagation Neural Network functions (BPNN) and Agent-Based Modelling and Simulation (ABMS). BPNN excels in capturing both linear and nonlinear time-series traffic data with multi-layer models. ABMS, a newer approach, divides the transportation system into interacting agents, providing a holistic view of traffic demand dynamics. AI's data-driven approaches often lack context, particularly in understanding spatial parameters, which limits their applicability in long-term forecasts. To make AI more competitive with traditional macro-modelling in transportation planning, new methods are needed to integrate spatial and temporal data effectively.**

Keywords—Road traffic forecasting; Transportation Planning; AI Modelling, Machine Learning; Agent-Based Modelling; Back Propagation Neural Network

I. INTRODUCTION

Traffic forecasting is a complex process affected by various factors such as road characteristics, urban growth, and population distribution. As urban areas continue to expand, transportation authorities face difficulties in effectively managing traffic demand. To overcome these challenges, researchers are exploring the use of artificial intelligence AI as an alternative technique to traditional methods to improve control and management of transportation systems with relatively simple and accurate forecast of traffic demand; However, accurate and reliable traffic forecasts remain a significant challenge due to the dynamic nature of traffic demand.

Current forecasting methods involve two main methods: wide range of basic to complex mathematical models, with generally, low accuracy, or macro-modelling planning methods which can reach sufficient accuracy, but they are known for their sophisticated procedures, time consuming and high cost.

The emergence of big data, driven by the collection and analysis of vast amounts of transportation system data, has made AI applications increasingly attractive for enhancing transportation design and operation. AI can play a crucial role in demand forecasting, which is essential for effective transportation planning. The advancement of sensor technology and communication systems has improved transportation monitoring. However, simply monitoring traffic is not sufficient for significant improvements in safety and efficiency. It is essential to utilize surveillance data for proactive management rather than reactive responses to achieve meaningful progress in transportation systems [1].

II. BACKGROUND

The term "Traffic Demand" is defined as the set of vehicles in a traffic system associated with the routes or directions from an origin to a destination [2]. Early attempts at traffic demand forecasting and transportation planning began in the 1920s, utilizing simple mathematical approaches that evolved into more complex models over time.

In recent decades, research efforts have focused on developing methods to improve the accuracy of traffic demand forecasts. This involves identifying the relationships between traffic demand and other planning parameters such as population, urban distribution, and land use. These relationships are represented by volume-delay functions (VDF), which capture realistic traffic patterns within the road network.

The concept of artificial intelligence AI was introduced in the 1950s and has gained popularity with the availability of big data and advancements in computing technology. AI holds promise for various fields, including transportation, by offering innovative applications and solutions. The improvements of mathematical functions have subsequently led to better mathematical models' results accuracy; however, the models' outputs remain highly sensitive to data variation inputs, especially when extending the target future range, given that these procedures have no data trend recognition, clustering cleaning or approximation approaches.

III. OBJECTIVES

The objectives of this review paper are to assess current applications of AI methods to ultimately provide alternative reliable traffic demand forecasts technique for urban areas by benefiting from the advances in AI machine learning methods, that requiring less efforts, cost and time compared to the commonly used transportation planning macro-modelling software.

Identifying and summarizing the current AI related traffic demand forecasting methods to provide an overview of the most recent AI related traffic demand forecasting techniques that have been developed and their respective strengths and weaknesses. This includes approaches based on machine learning algorithms such as artificial neural networks, support vector machines, and decision trees, as well as hybrid models that combine these algorithms with other methods.

Moreover, to evaluate the potential of AI based traffic demand forecasting methods to improve transportation planning by providing accurate and reliable forecasts of future traffic demand.

IV. METHODOLOGY

The methodology followed to develop this review paper is the systematic review methodology, as it is comprehensive method for identifying, evaluating, and producing all available relevant evidence extracted form available literature. A comprehensive search of technical papers, journals, books databases, conference proceedings, and other sources is conducted to identify all relevant studies. The extracted data and information are analysed and the findings of the systematic review are interpreted and reported in a clear and standard format.

V. EARLY RESEARCHES OF AI APPLICATIONS

Several pieces of research have explored the historical background of early AI applications in transportation which date back to the first half of the last century. In the Transportation Research Conference, a paper titled "Artificial Intelligence in Transportation" was presented by A. Sadek, in which he noted that, in the early 1950s and 1960s, AI researchers often adapted lofty goals such as the development of general-purpose problem solvers.

The general research objectives, however, have evolved since to more specific goals which address real transportation problems that have been quite challenging to solve using traditional and classical solution methods [3]. During the late 1960s and early 1970s, there was a notable shift in transportation planning concerns, prompting the development of problem-solving models. However, the earlier models exhibited a strong bias towards highway planning and posed challenges when applied to regional forecasting for alternative solutions involving significant modifications to the transportation system. In the 1970s and subsequent decades, a fresh perspective on travel analysis emerged with the introduction of different choice models for understanding travel behaviour. AI applications primarily concentrate on choice modelling, as it constitutes a crucial element in more modern travel demand models [4].

Based on over a thousand source records of the European Communities programme (DRIVE), Bielli explored the applicability of artificial intelligence in the traffic and transportation field, concluding that AI applications have a promising role in solving transportation and traffic related problems [5]. Since the early 1990s, AI fuzzy sets have been employed to bridge the modelling gaps between normative and descriptive decision models in related travel behaviour research. [6].

Artificial intelligence functions can be broadly classified into two categories: "strong" AI, which closely resembles intelligent human reasoning and exhibits self-awareness, and "weak" AI, which focuses on specific application domains, possesses practical knowledge like expert systems. However, the distinction between strong and weak AI functions is not rigid and often blurs, as certain functions may transition from one category to the other [7].

VI. RECENT RESEARCH OF AI APPLICATIONS

The inherent advantages of AI algorithms, such as their ability to bypass assumptions about underlying model formulations and handle uncertainties in parameter estimation, have encouraged researchers to investigate various AI techniques for accurately predicting traffic demand under diverse future scenarios. Some notable algorithms in this domain include K-nearest neighbour (KNN), Support Vector Machine (SVM), Random Forest (RF), regression, and Artificial Neural Network (ANN) [8]. Agent-based modelling and simulation (ABMS) is a modern AI approach for modelling complex systems, which involves dividing the transportation system into a collection of interacting agents. This method considers various elements, such as vehicles and land use, as individual agents governed by simple rules. As depicted in Figure 1, ABMS modelling stands out due to its ability to incorporate various factors influenced by roadway geometry, and the impacts of individual learning in transportation modelling [9].

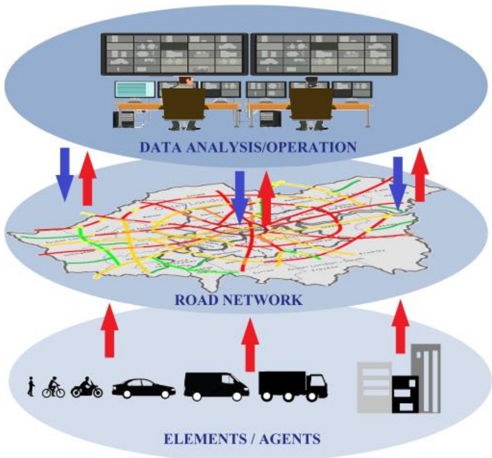

Figure 1: Agent Base System Layers Illustration [9]

Considering the combination of current traffic situation and a set of historical data, Rice and Zwet developed an artificial intelligence neural network model for travel time forecast. Their research identifies a linear relation between the variables used to predict travel times [10].

Genetic algorithms in AI have been used to study route-choice modelling, aiming to understand the dynamic nature of driver-network systems. This approach involves employing microsimulation tools to develop a theoretical model that encompasses drivers' cognition, learning, and route selection. Furthermore, it considers the inherent limitations in drivers' cognitive abilities [6].

AI can enhance travel demand modelling in two key ways. Firstly, it offers a perspective on model selection that prioritizes the model's predictive capability over its ability to fit training data. This approach recognizes the potential issue of overfitting, which must be tackled to ensure the model's predictive performance remains intact [4].

Public transportation analysis encompasses various aspects, including planning, design, operations, and policy-making. By formulating the problem as a multi-objective optimization, AI enables efficient decision-making that considers multiple factors simultaneously [11].

Intelligent transport systems ITS applications, including variable traveller information, dynamic route guidance DRG, and urban traffic control (UTC), mainly rely on data collection systems [12].

In his research on traffic forecast, Ahmed employed a machine learning approach to utilized a comprehensive dataset spanning seven years, sourced from the UK National Traffic Information Service NTIS, as well as an average annual daily traffic (AADT) dataset managed by the Department of Transportation (DfT). The research highlighted the significant advantage of deep learning techniques, which offer adaptability and continuous model training. This adaptability makes deep learning an ideal solution for tackling big-data problems effectively [13].

In his research titled “Multimodal machine learning for intelligent mobility,” Roche noted that the use of recent advances in digital technologies improve transportation systems’ efficiency, which is referred to as intelligent mobility and is one of the principal beneficiaries of data driven solutions; this is due to the significant complexities of real-world systems operation, as it is impossible to program decision making logic for every eventuality manually [14].

The potential application of Artificial Intelligence AI in the field of transport was explored by Miles and Walker, in their research study titled “The Potential Application of Artificial Intelligence in Transport” published in 2006. The authors emphasize the role of AI techniques in enhancing decision-making processes in real-time transport operations, such as traffic management and service delivery [15].

Similarly, the rapid developments in AI and their potential applications in the transport sector was discussed by Abduljabbar et al. in 2019. His paper emphasizes the innovative computational methods inspired by the human brain that AI brings to the field. It addresses the challenges posed by increasing travel demand, emissions, safety concerns, and environmental degradation in the transport industry [16].

In their research published in 2019, titled “Development of Traffic Volume Forecasting using Multiple Regression Analysis and Artificial Neural Network”, Duraku and Ramadani developed a traffic volume forecasting model for the Anamorava Region. The study's outcomes provide practical insights for transport planning strategies and highlight the effectiveness of the PCA-RBF model in traffic volume forecast [17].

In 2019, Kolidakis, Dimitriou, and Pallis conducted a study comparing a hybrid methodology that combines Singular Spectrum Analysis (SSA) with ANNs to conventional ANN for time series analysis and forecasting of road traffic volume. The research aimed to develop short-term forecasts of daily traffic volume at toll stations along the Greek National Highway Network. The study suggests that the SSA-ANN hybrid model enhances the accuracy of daily traffic volume forecasting compared to conventional ANN models [18].

In their research titled “A Review of Traffic Congestion Forecast using Artificial Intelligence” published in 2021, Akhtar and Moridpour conduct a systematic review of research conducted on traffic congestion forecast using artificial intelligence AI, particularly machine learning models. They emphasize the potential of deep learning algorithms in assessing large datasets and mention the need for further exploration of various machine learning algorithms [19].

The research paper titled "Graph Neural Network for Traffic Forecasting," authored by Jiang and Luo in 2022, introduces the application of graph neural networks (GNNs) in traffic forecasting. The authors emphasize the significance of traffic forecasting within intelligent transportation systems and discuss the utilization of deep learning models like convolutional neural networks and recurrent neural networks [20].

A research study titled “Modern Trends in Artificial Intelligence in the Transport System,” in 2022, Okrepilov et al. investigate the application of artificial intelligence AI technologies in the transport system. The authors emphasize the need to find the optimal balance between process automation and the improvement of labour content, with a focus on increasing the role of humans in managing the application of AI technologies for societal benefit [21].

To address the problem of traffic flow forecast and propose the use of a Bi-GRU model, Wang et al. in 2022 used real case data comparison with benchmark models for the evaluation and assessment. The results demonstrate that the Bi-GRU model outperforms other models in terms of forecast accuracy, indicating its effectiveness in capturing the sophisticated non-linear temporal characteristics of traffic flow [22].

Comprehensive review of machine learning (ML) and deep learning (DL) techniques applied in traffic flow forecast were conducted by Sayed et al. in 2023 titled “Artificial Intelligence-Based Traffic Flow Prediction: A Comprehensive Review”. The study's contribution to the literature lies in its consolidation of existing knowledge and the identification of emerging trends and opportunities in AI-based traffic forecast [23].

Similarly, Shaygan et al. in 2022 provide an in-depth overview of recent advances and emerging research opportunities in AI-based traffic forecast. The study's focus on multivariate traffic time series modelling highlights the potential of AI in improving forecast accuracy. The identification of challenges and suggestions for future research directions emphasize the need for intelligent and robust traffic forecast methodologies to address traffic congestion and optimize transportation systems [24].

The research titled "Deep Learning for Intelligent Transportation Systems" by Veres and Moussa investigated different neural network architectures' learning ability, including multi-layer, sequence and spatial representation structures as shown in the Figure 2, and found that multi-layer neural networks are the most common neural networks architectures. This model works with vector-based data representations [25].

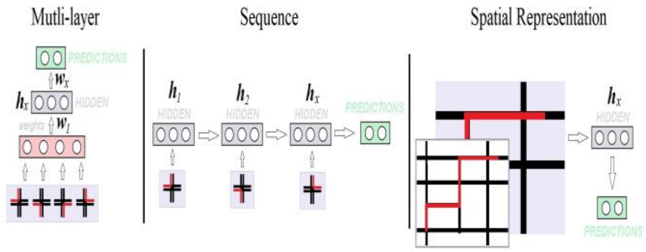

Figure 2: Different Learning NN Architectures [32]

VII. SPATIO-TEMPORAL AI FORECAST MODELS

Due to its relatively-high complexity, fewer researchers investigated the possibilities of artificial intelligence applications in developing spatio-temporal models.

In 2023 Cui et al. conduct a critical review of spatiotemporal correlation modelling approaches in machine learning based ML-based traffic state forecast in their research paper titled "Spatiotemporal Correlation Modelling for Machine Learning Based Traffic State Predictions State-of-the-Art and Beyond". This study contributes to advancing the understanding of spatiotemporal correlation modelling [26].

The integration of multiple neural network architectures and attention mechanisms enables the model to capture spatio-temporal characteristics effectively was proposed by Lu et al. in their research paper published in 2022 [27].

Exploring more than a hundred research articles and books in 2022, Behrooz and Hayeri conduct a literature review to evaluate the application of machine learning ML algorithms in surface transportation systems. the review suggests that sophisticated ML algorithms have been underutilized [28].

VIII. AI AND TRADITIONAL COMPUTING METHODS

In a research paper published in 2012 titled "Difference Between Artificial Intelligence and Traditional Methods," Zuylen found that both methods describe the relationship between independent and dependent variables, albeit in a more heuristic manner [7].

Figure 3 illustrates the overall procedure of using an artificial intelligence neural network-based approach for data input and processing that include training and testing of the structured model to obtain the required forecast results with identified accuracy.

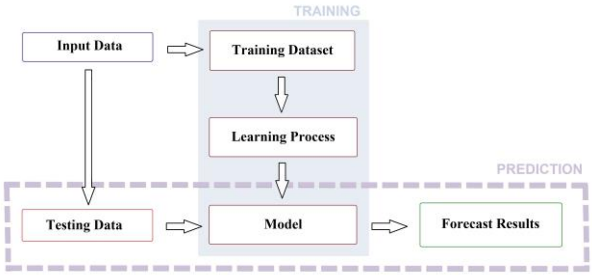

Figure 3: General Process of AI NN-based Method [7]

Training neural networks necessitates substantial amounts of data to effectively learn relevant patterns and abstractions. Additionally, it requires sufficient computational resources to process the data efficiently.

Data training and learning processes also make artificial intelligence methods a unique and more flexible method to analyse data and obtain forecast results with higher accuracy compared to other traditional computing methods.

IX. SHORT-TERM AND LONG-TERM FORECAST

Short-term traffic forecast is a complex field due to the multitude of factors that can impact the performance of forecast models. All of these elements contribute to the intricacy of short-term traffic forecast and require careful consideration when developing accurate models [12].

Traffic forecast research often defines short-term forecasts as ranging from seconds to hours, focusing on vehicles already on the road. Long-term forecasts rely more on spatio-temporal and land use data. However, there's no consensus on what constitutes short-term or long-term, and criteria for classification vary [31].

The research on "Short-Term Traffic Volume Forecasting with Asymmetric Loss Based on Enhanced KNN Method" examined the effectiveness of a newly designed algorithm based on the KNN model for short-term traffic forecasting under normal conditions. Unlike the traditional KNN algorithm, the proposed algorithm demonstrated improved accuracy in traffic forecasts, particularly when there was a notable difference in the cost of residual direction [8]. Meldrum and Taylor conducted a study on long-term traffic forecasting using an AI approach. However, achieving longer-term forecasts proved challenging due to the unpredictable nature of inputs over extended time periods and distances, making accurate forecasts more complex [29].

X. LIMITATIONS OF AI APPLICATION

The limitations of available AI software and the challenge of predicting traffic in irregular conditions, such as accidents or weather, hinder accurate forecasting. Complex factors like signalization and temporal variation of traffic distribution further limit forecast span. Another drawback is the difficulty in interpreting AI model results, reducing transparency. To address this, graphical representation software could be developed to visually demonstrate variable contributions, enhancing transparency and understanding of outcomes [4].

One major criticism of many AI algorithms, which was previously referred to by Zuylen, is their tendency to be perceived as black boxes. This raises concerns about their ability to generalize the model to situations that were not adequately represented in the dataset [30].

X. NEURAL NETWORK FUNCTION SUITABILITY

The AI back propagation neural network (BPNN) function is considered for this research due to its suitability to the data analysis type of traffic demand forecast based on the recommendations of several researches. In their 1993 research paper, S. Edmund and C. Roger Chen made several noteworthy observations. Firstly, they found that three-layered backpropagation neural networks are well-suited for time series forecasting, particularly for capturing temporal relations. However, they also acknowledged the complexity of training such networks limits their practicality [31].

In the field of deep learning, many studies have adopted the approach of training models to predict demand by incorporating spatial and temporal patterns. This is typically achieved by combining various network architectures designed to process different types of data modalities. [9].

Meldrum and Taylor conducted a study to evaluate an AI application method that utilized a fuzzy logic ramp metering algorithm combined with an artificial neural network model. The model was able to provide reliable forecasts to compensate for missing data [29].

A study conducted by Ishak and Alecsandru in 2003 investigated different neural network models' structure approaches to optimise short-term traffic forecast performance on freeways. This study found that no single structure outperformed the others [32]. Significant progress has been made in addressing overfitting in artificial neural networks and ensuring their projecting validity [2].

XI. CONCLUSIONS AND FI NDINGS

The application of artificial intelligence in traffic forecasting is showing significant promise, but also faces challenges that need to be addressed. Key elements in developing an effective AI model for traffic forecasting are the choice of input traffic variables, analysis methods, and model structures.

Advances in deep neural networks (DNNs) and machine learning (ML) have led to improved data classification and behaviour recognition. Data validation remains critical, as does the need for valid datasets suitable for processing.

A major challenge that faces AI application in traffic forecasting is the long-term forecasts, particularly on freeways, however, two functions: Back Propagation Neural Network (BPNN) and Agent-Based Modelling and Simulation (ABMS) offer promising tools for longer-term linear and nonlinear traffic forecasts, especially when spatio-temporal data is considered. Techniques such as cross-validation and random subsampling have helped mitigate issues of overfitting in neural networks, thus improving predictive accuracy.

Artificial intelligence potential applications in the broader transport sector, including Intelligent Transport Systems (ITS), is substantial as it can enhance decision-making, improve user experiences, and optimize real-time transport operations. Several AI-based models like Cascaded Artificial Neural Networks (CANN), Bi-GRU, and Deep Ensemble Neural Networks (DENN) are emerging, which consider factors like spatial correlation and external influences for improved accuracy in traffic flow and speed forecasting.

Furthermore, the integration of methodologies like Singular Spectrum Analysis (SSA) with Artificial Neural Networks (ANN) and graph neural networks (GNNs) is contributing to higher forecast accuracy. Despite these advancements, the field faces limitations such as the absence of clear problem definitions and the need for open-source platforms and high-quality spatio-temporal datasets for collaborative research.

Deep Learning (DL) techniques have shown considerable success in forecasting traffic flow and congestion. However, there is a shortage of AI software specifically designed for road traffic behaviour and forecasting, representing an area in need of further research.

There are already several real-world applications of AI traffic forecasts, such as Google's traffic maps. Furthermore, it was illustrated that the AI applications can improve several traffic aspects such as traffic safety by real-time monitoring and predictive analysis.

AI systems implementation costs can be significant due to hardware and software requirements, also, AI could automate certain jobs, on the other hand, it could also create roles in data analysis and system maintenance.

Compared to traditional methods, the ethical concerns of AI applications in transportation planning may arise from data privacy for some sensitive or personal data used in the AI model development.

While AI holds great promise for optimizing transportation systems, public transport routes and enhancing traffic flow and efficiency, more research is needed to assess its economic benefits and productivity gains. Importantly, bridging the gap between spatial and temporal data will enable AI to compete more effectively with traditional macro-modelling techniques in long-term traffic forecasting.

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