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Chapter 6: Creating self-optimizing, adaptive routing architectures through artificial intelligence-assisted traffic analysis and response systems

6.1. Introduction

Artificial intelligence (AI) and particularly machine learning methods are finding their way into traffic management, as in many other fields (Mao et al., 2018; Bega et al., 2019; Sun et al., 2019). Especially about autonomous vehicles and decentralized communication, efficient management of the data exchange in a network is a key challenge for the future. Many present research projects address this point by performing data management in a central instance. Nevertheless, to enable and provide highly reliable traffic systems that should operate 24 hours a day and 7 days a week, a centralized instance may be a potential weak point. Solutions could be composed by combining AI-based traffic analyses with self-regulating network components; these might be point-to-point connections, for instance, between two vehicles or between a vehicle and a back-end server. Advancements in technology have long sought innovative solutions for traffic management, considering new approaches involving artificial intelligence, especially machine learning methods. The pervasiveness of cities and hence traffic congestion everywhere calls for road and vehicular traffic management innovations in every possible aspect. More importantly, increasing traffic intensity is anticipated as cities grow denser and populations increase annually. Traffic analysis is crucial for the development and management of any routing system. When traffic intensity in a network increases, the importance of studying possible traffic solutions and traffic analyses in general also augments. While there is a significant amount of incoming vehicles from one area to another, traffic congestion and traffic management have to be taken into account. Time being a critical factor in day-to-day life, traffic should manage intense vehicle flow so that the overall travel time of passengers is minimized. Thus, our study is not only resourceful but also timely to address since it manages vehicular traffic crowding efficiently.

6.1.1. Overview of the Study

The research presented in this paper seeks to demonstrate the potential of using different techniques of AI-based traffic data analysis and processing to increase the effectiveness of routing in urban and inter-urban road transportation. First, we apply a pre-trained classifier to a large dataset of real data in a first screening from the point of view of the applicability of deep learning to the problem and simultaneously cross-validate the classifier's performance in processing real data from traffic speed sensors at the same time. Other and more advanced deep learning architectures are then applied to the candidate data. Finally, a neural network for system identification and long-term forecasting is trained and used to simulate a traffic control system that is easier to test for a route planner by comparison to the real system.

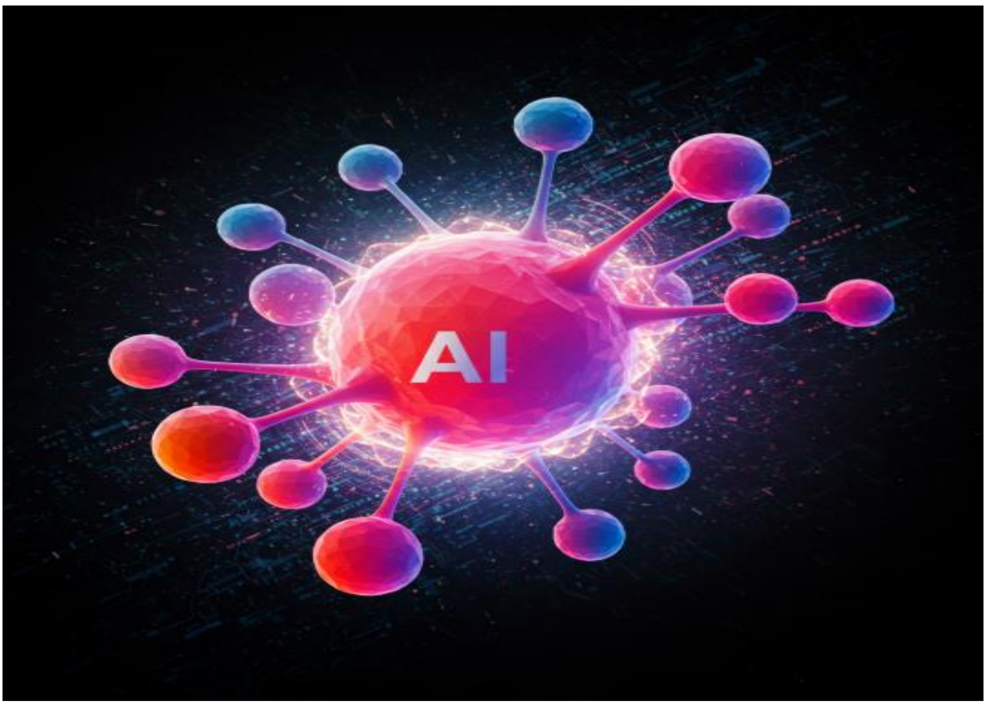

Fig 6 . 1 : Adaptive AI

The main steps in the study are summarized. Before introducing the proposed study, however, the rationale needs to be presented. Traffic can be studied as a complex system, using modern control theory, and it is possible to identify road traffic control systems designed to control traffic flows from a centralized traffic control system architecture down to simple non-sequential traffic lights at an intersection. In parallel to this centralistic approach, an alternative vision studies traffic control and routing from a general systems architecture point of view, in which the center of attention is the self-optimizing and anti-fragile entity that emerges from the interaction of vehicles in the network, and identifies the system components and dynamics at each anniversary level. Reported herein is a traffic analysis that implements AI/ML-based tools to identify traffic flow state types and generate future states. The system is effectively attacked by sensor failures, with a significant impact on the capability of the AI/ML model to analyze and generate traffic states. System updates and control actions can be simulated in response to attacks.

6.1.2. Objectives and Research Questions

The main objective of our research is to point out new paths to improve established routing strategies that are widely used in today's communication networks. Therefore, we first have to identify their respective weak points and the requirements for enhanced techniques in detail. In essence, traffic shall constitute the actual driver rather than routing protocols or the network infrastructure when it comes to optimizing data transport within telecommunication networks. We are confident that the current attempts to provide perspectives on self-optimizing networks feature a strong prevalence of routing and the design of a new simplified protocol that is capable of introducing route allocation decisions according to the traffic state.

In this context, the approach of using AI technologies for traffic management offers a holistic albeit decentralized traffic management approach, which has not been attempted yet in the field of traffic management. The research group is convinced that the interrelation between routing decisions and respective traffic properties, the degree of topology availability at the packet forwarding components, as well as the emergent behavior of large networking systems, in general, are issues that need a deeper understanding in one complementary investigation. From these deliberations, we derive the research questions that guide our investigation: how can AI techniques influence and frame traffic management processes? Which parts of traffic management can or should be determined by AI-based methods, and what are the scopes for future work?

6.2. Background and Motivation

This study focuses on creating deep learning-based models and routing strategies for sustainable urban traffic. We postulate that the development of innovative systems for urban traffic is of great importance due to both its historical value and practical use case. In a series of historical accidents, self-sustained traffic waves, which are still part of reality today, were analyzed for the first time in the 1950s. Intelligent intersections in urban transportation were proposed. More recently, it was proposed to implement dynamic traffic lights to reduce waiting times at junctions. There are several reasons why the investigation is highly motivated. In all large cities, traffic congestion is a major problem. Consequently, the inefficient use of transportation networks gives rise to reduced transportation performance due to empty vehicle seats. New ways to improve traffic congestion are claimed, especially by the rapid growth of urbanization. In the multidisciplinary research on intelligent routing, traffic analysis, and transport flow control, we look into mobile research. Traffic planning is essential for transportation technology and urban planning. Modern urban transportation systems include individual cars, buses, bikes, etc., which have a fundamental feature: self-organization.

Self-optimizing routing is also important for developing intelligent transport systems, including driverless vehicles and charging cars. Electric cars must be alerted optimally in all areas, including cost and charging station range. Wireless charging on motorways, thus incorporating the charging strategy, was likely to increase urban acceptance. However, if the current traffic is not considered, the estimation of acceptance will be coarse. Furthermore, ensuring traffic efficiency will avoid negative feedback from endurance drivers and the generation of noise and air pollution in cities, thus encouraging greater acceptance. These are the major challenges in urban transportation and road traffic forecasting and management. Consequently, it is apparent why a large amount of traffic research has been carried out.

6.2.1. Rationale Behind the Study

The interest in the development of multimodal transportation systems in major urban environments is a direct consequence of the factors linked to the ever-increasing traffic volume. This trend should be countered by a more responsive and adaptive traffic system, which continually adapts to the traffic state. However, the current general approach to these systems consists of simple, static, shortest-path-based routing algorithms that do not represent a valid solution for such a context, due to the sensitivity to small perturbations underway. This study goes in the direction of numerous attempts to develop new self-optimizing routing architectures that benefit from the many evolutions of our connected environment.

In light of this problem, we have to point out the need for a global cooperative approach, as currently deployed traffic analysis algorithms still focus on localized solutions. It has to be discussed how traffic prediction can effectively be used to envision the incoming state of the road section under examination. Regular traffic routing merely tries to alleviate the build-up of traffic, albeit this solution often comes after the fact. AI can potentially support all stages of traffic analysis-based decision-making, aiding the full process from the detection of the current state to the optimally projected state for its evolution over time. This work finds alignment in the emerging AI-assisted trends and, as well, in smart city development, rigidly oriented towards more innovative solutions to problems of our everyday life, in particular transport issues. Overall, the primary goal and objective, aside from the research interest, is to provide the community of interested stakeholders with a theoretical protocol further involving AI-assisted solutions and how to deploy them in developing new standards.

6.2.2. Justification for Research Focus

The current state of the art in the field of traffic management offers ways to reduce traffic, which can be categorized broadly into two approaches: traffic reduction and delay reduction. Our research is in the category of delay reduction, specifically on routing improvements. The focus of our work is developed considering the limitations in the existing solutions for traffic management; both local and non-local methods are at a high advantage with AI integration and should be investigated since no comprehensive ones are available. We believe that routing architectures can be significantly improved through AI integration to allow for the realization of efficient traffic flows. There is a growing demand for versatile models to perform real-time processing of large-scale traffic data and provide advanced predictions for profitable decision-making. The global expansion of transportation networks has increased the need for advanced traffic management. With the increasing field of big data, software, and hardware technology improvements are now able to significantly increase real-time analytics capabilities for traffic monitoring, anomaly detection, and predicting degradations in case of equipment failures. Such all-in-one self-optimizing systems are particularly demanded in large metropolitan areas, as the complexity of the systems grows. A new trend initiated by government initiatives in various countries is driven by the need for sustainable development and intelligent city management. Urban transportation systems, when integrated with AI, are referred to as intelligent transportation systems. AI-assisted traffic management has the capability of responding dynamically to current events, such as adverse weather conditions or accidents.

6.3. Literature Review

Due to the continuous increase in Internet traffic, novel systems are required to manage the huge overload of information to guide the Internet's limited capacity and efficiently route traffic. Most notably, today's proposal for traffic routing routes Internet traffic following the shortest path in terms of the number of Autonomous Systems (ASes). Despite its apparent simplicity and widespread utilization, current approaches working on the management and control plane face significant inefficiencies and produce suboptimal routing conduct, even without considering the missing AS-path visibility. In this regard, several options have been considered, each providing new insight into how traffic should be routed, but all share common pros and cons.

Substantial investigation has additionally been performed on traffic optimization mechanisms; essentially, these systems are predominantly focused on reconfiguring and reallocating the network's resources. Last but not least, several studies have investigated the use of AI techniques for understanding and proactively optimizing various aspects of Internet traffic, compared to the routing architectures discussed above. These approaches may provide significant benefits, such as real-time data analysis that would allow traffic engineers to automatically take prompt actions or early adaptive behavior to optimize traffic flows and route hijacking detection. However, there is a distinct lack of research that investigates the use of AI on traffic data at network nodes in real time to generate insights that may aid distributed routing. The question is whether such a study will be of use and whether it can be correctly defended.

6.3.1. Existing Traffic Routing Methods

Traditionally, network traffic is routed using shortest-path routing algorithms. When not efficiently managed, this strategy can result in severe traffic spikes and delays, which can have expensive consequences. Many proposals enhance the routing process in WDM systems employing static traffic matrices, e.g., through Real-Time Impairments awareness. Many of these are tuned to perform effectively with static traffic demands, yet when demands vary, their enhanced performance is not guaranteed. The extensions are made with knowledge of how well network conditions can be anticipated under stable traffic conditions. As traffic can be highly variable, these methods may require continuous updates or adaptability features to operate optimally.

The popularity of dynamic routing for control plane architecture is evident. As traffic patterns change, dynamic routing mechanisms can respond by adapting the allocation of network resources. Another method of traffic routing relies on the predictability of traffic demands. Further, attempts can also be made to improve predictability. From a control plane perspective, the most significant feature in this context is the level of adaptability. SDNs create traffic routing proposals that are effective due, in part, to their ability to react to these real-time observations. There are several adaptation strategies to address the impact of real-time data. Analysis of previous blockage and delay adjustments can also be used for diversions. Coordinated control of all active lightpath resources can also be used to reduce physical clashes. Per-node duplication can make a trade-off between traffic duplication costs and path diversity benefits. Finally, dynamic circuit adjustment over an existing network can provide paths with minimized latency. Further, these can often be designed to directly recommend or modify traffic demands, requiring user involvement. The former is dispreferred if congestion occurs, as these typically result in lost user demand and will not improve network suites for existing traffic.

6.3.2. AI in Traffic Management

Today's traffic management reality is shaped by artificial intelligence, which by its very definition encapsulates all possible techniques for the computer to distinguish logical patterns and rules by identifying relationships and concepts between input data points. Machine learning, both supervised and unsupervised, is deeply rooted in traffic prediction these days. Most modern congestion detection systems employ extremely sophisticated machine learning algorithms that predict the traffic congestion that is most likely to happen. The main advantage of AI lies in the fact that it is possible to sift through immense amounts of data and attempt to identify small trends that influence the output. At its zenith, AI in traffic management can process vast amounts of data related to traffic and uncover trends, patterns, and other detailed information hidden in that data (Wang et al., 2020; Ventre et al., 2021).

Its capabilities and limitations are complementary on many levels, specifically when we touch the human aspect of driving, which might seem unpredictable at times. Gathering driver behavior from a large number of samples, such as people's travel logs, can help traffic engineers find alternatives on how to guide humans. It tries to minimize prediction errors and succeeds in avoiding intersections it thought would have serious traffic. However, using prediction data to design and alter road systems via heuristic methods is a leap that existing implementations don't take, which is something we wish to address. Heuristic methods currently in use work by taking the entire traffic load into account and looking at results that would be obtained if the drivers followed algorithms built into the model. AI, based on past data, does capture successful human behavior in traffic, but seamlessly integrating what it finds with currently in-use systems is something we envision will be complex and require extensive study.

6.3.3. Challenges in Current Systems

Currently, a majority of traffic systems work with nothing but predictions and historical data that, in most cases, are neither accurate nor representative. This results in poor adaptability to current situations, such as increased mass events, construction sites, traffic accidents, technical problems with trains or elevators, and overcrowded buses or vehicles, to name just a few. Before users can adapt or the situation changes again, most traffic systems are already overloaded, leading to increased individual travel times, which again results in a reduction in the capacity of the already tight infrastructure through the use of a single individual. Conventional routing methods are therefore extremely inflexible, which is easy to see, as the emergence of various ride-sharing and mapping services in many cities has not led to a demonstrable and sustained reduction in traffic congestion.

Even with all the data that is generated every day and, in the future, will be available in even larger volumes due to the spread of new technologies and multi-sensor networks, most of it is not used. Finally, current solutions, such as public transportation and more bicycle lanes, are also an issue for which data is needed to help make urban areas more attractive and create a smart territory. These issues can be mitigated by using AI in the context of transport, urban, and traffic engineering. Additionally, cities do not yet use automated methods, such as reinforcement learning and distributed systems, in the day-to-day operation of their transportation systems. Nonetheless, the state-of-practice traffic engineer of each city is, in general, not ready or inadequately prepared to design AI-based or AI-assisted systems. To some extent, this is a technological challenge, but many barriers are social, political, and legal reasons.

6.4. Theoretical Framework

To situate the present research, it is necessary to introduce its theoretical framework. In keeping with foundational studies of self-optimizing structures, the design and architecture of the Internet as an intelligent whole system can profit from an understanding of adaptive systems theory. Placed at the field's intersection of sociology and artificial intelligence, the principles of adaptive systems, which elucidate self-optimization, can inform the development of other elastic, self-organizing systems such as wireless DRP, network commodity supply indices, or Internet advertising markets. While less studied in the AI literature in comparison to expert systems or agent-based systems, traffic management is a burgeoning concern for these networks, in part because it is difficult to get aggressive about utilizing even desired traffic, given the contracting costs of network resources.

Whether based on fuzzy or Petri net models, an increasing number of traffic engineering works incorporate machine learning techniques into traffic inference systems. In areas of significant overlap with this work, machine learning has or is planned to be integrated into routing, traffic engineering, and resilience operations. While mostly tangential to traffic inference, three papers have addressed the use of machine learning in demand prediction. By contrast, this paper targets the purely exploratory task of learning to distinguish congestion, as opposed to predicting the next level of congestion. Optimal lane-changing strategies also go after the identification of such bottlenecks, but from the driver's point of view, an exclusively empirical assignment. The architecture described in this work, on the other hand, is the first to focus on predicting congestion as an input into global or local self-optimizing or traffic forecasting systems.

6.4.1. Adaptive Systems Theory

Traffic management – like many distributed monitoring and control contexts – may be described in the language of adaptive systems. An adaptive system can accommodate and adjust to variations in its inputs, parameters, or internal states, in some sense retaining optimal performance or behavior. Indeed, the success of adaptive systems in responding to rapidly varying conditions is universally evident. The root property of an adaptive system is flexibility: the ability to reconcile the demands of an environment without taking frequent recourse to central control. The push for distributed and decentralized traffic management systems relies on the need to reconcile large equipment investments with the rising expectations concerning service quality, safety, mobility, and environmental performance.

Fig 6 . 2 : Self-Adaptive Traffic Signal Control System Based on Future Traffic Environment

Self-optimizing routing architectures are intelligent, adaptive systems, whose behavior under worst-case assumptions can be evaluated by first considering the idealized case introduced in the rest of the text. In the ideal special case at hand, the demand at each entrance arrives at a unique exit, and to move forward it must first cross an internal intersection. The presented traffic light schedule exactly realizes the following function: at any combination of moments where the demand arrives at a new intersection, or anticipation remains from the last arrival, determine the optimal sequence of the next pair(s) of green lights for that particular entrance. Any adaptive system consists of two components: a black box (the actual adaptive system) and a white box, which is capable of determining the input-output relation of the black box or may, additionally, act as a model for it. In our case, the black box is an intelligent, adaptive traffic management system, and the white box is a set of AI modules capable of predicting its behavior, input-output relationships, and of course enforcing it to yield desired outputs.

6.4.2. Machine Learning Fundamentals

Machine learning can be understood as a branch of AI that encompasses the ability to learn from existing datasets and make decisions based on newly observed data without explicit programming or supervision from humans. Machine learning is composed of two subcategories: supervised and unsupervised learning. About the types of machine learning, reinforcement learning is applied to optimize decision-making based on learned data. Machine learning algorithms are formulated to minimize major issues such as computational complexities and maximize success rates.

In the field of traffic research, machine learning has been widely used in the prediction of traffic behaviors for decision support. The advent of machine learning has significantly improved predictive modeling techniques. Machine learning has received considerable positive attention due to its capability to carry out inferences on hidden patterns, thereby facilitating the decision-making process. Machine learning can potentially enhance LAN mouse prediction of high-performance computing workloads. Machine learning algorithms are known for their ability to learn hidden patterns and make predictions automatically. However, when these automatic predictions are applied to the real world, they often face several challenges in practical applications due to unstable output and various deterministic factors.

The context of a traffic phenomenon in the domain of network science is used to introduce recent challenges to machine learning used in traffic studies. Since crucial delimitations on routing have been relaxed and data capacity has increased, a self-optimizing network that can autonomously adjust parameters in virtual links for rerouting purposes has been proposed. Such a network will make automated routing decisions for which tools are needed that can analyze traffic flow data.

6.5. Methodology

We used passive probe monitoring to collect data from emulated production server traffic. We readily process this data with traffic analysis algorithms, which let us directly infer the detailed real-time topological information we need. This technique works in a computer simulation of our deep learning-based genetic algorithm for finding self-optimizing routing architectures in real time.

We have divided the AI/TP into three overarching segments. In each sub-section of this document — AI-Assisted Traffic Analysis for Predicting and Disentangling RT Path Diversity; Reconstruction-Free Traffic Matrix Estimation using Variational LSTM Autoencoders; and Algorithmic Traffic Analysis — we present the pipeline used in our AI/TP and answer the ‘why’ of the selected pipeline.

Two blocks are required to construct the AI/TP for predicting the path diversity flows (PDFlows): 1) Preprocess and process the algorithmic blocks used to select flow blocks of data input; and 2) For each selected block of data, predict the PDF of the corresponding EPDF. Given: a block of randomly selected traffic data; a statistical model that is trained on the reference traffic data and can predict the probability distribution of an arbitrary flow packet's path; and 3) Traffic data that is structured into binary matrices. Then: we select the flow direction in which to create a block. We select N contiguous flows of traffic, where N is determined by the maximum number of flows that we can preprocess in step 1. With experimental setup and enumeration of heuristic algorithms, this section introduces the design of each of these building blocks in great detail.

6.5.1. Data Collection Techniques

Data Collection for Traffic Analysis and Traffic Models

Analyzing how data is collected is as important in analytics as analytics itself. There is a lot of literature on data gathering, and surveys are a common data collection technique in the operations management literature. For the present paper, collecting traffic data can either be through observational study while on location or an online tool to record visits. Alternatively, an appropriate choice of methodologies can be implemented. These include analyzing, visualizing, and evaluating data. Findings can be used to promote SRAs, consult a national boundary, or inform international traffic management meetings. Compared with traditional construction methods of SRAs, which can be costly and time-consuming, gathering and analyzing feedback data using online systems, and then putting in place measures to mitigate shortcomings, is a cost-effective method of traffic analysis and dissemination.

The technologies used in traffic research need to obtain high-quality raw data such as speed, accelerations, location, traffic light timings and controls, right-of-way rules to solve questions about the behavior of the transport system, traffic planning, haptic data feedback, avoiding response bias, safety, risk, and the ethical admission of AI adaptive pilot vehicles to share a road network. Consequently, the following technological capabilities to systematically collect a wide range of variables were included in the range of modern smartphones, GPS, radar, vision, phone data, and haptic data. Data can be acquired through video, image, audio, and other sensory acquisition methods. For traffic scenarios, the appropriate use of phone data and various types of smartphone sensor data collection such as GPS, accelerometer, haptic data, edge computing, and combined data feeds are 21st-century capabilities. Each has its limitations. This includes the choice of radar and USB radar connected to a laptop to be used on a bike. Various considerations include these limitations. In this section, this research presents several methods for conducting road traffic data collection. This research initiative examines data collection techniques used to collect real road traffic data as part of a study to develop self-optimizing routing architectures for adaptive pilot systems. Furthermore, a range of attempts and misgivings to collect data in different traffic conditions are highlighted.

The focus is on the approach to collect free-flow traffic data from an important blind corner with subsequent evaluation of the traffic environment. The technical solutions to collect data with adapted experimental setups are discussed, along with the methodological changes to record terminal trip times. These changes were initiated in the face of collected data quality, offering inadequately informative selections, culminating in data dropouts. Data collection methodology can be divided into three categories: surveys, observational studies, and opportunistic exploration. The latter approach may include counting sensors, interviews, etc., and technology-driven possibilities in this category enable real-time data acquisition over the Internet. The technology-driven method is employed invariably with additional methods to test its appropriateness and representativeness. Data collection for modeling requires observations at different times, in different locations, for different percentages of traffic flow within the existing infrastructure domain.

6.5.2. Traffic Analysis Algorithms

Traffic analysis (TXA) algorithms process and analyze the data collected to improve the overall network traffic control and routing performance, either in real-time as part of the traffic management process or offline for management and resource re-dimensioning purposes. The large amount and variety of data that are collected to properly support the overall traffic optimization needs, together with the resulting complexity of the algorithms and methodologies, provide the science and technological area of traffic analysis with a wide and continuously updated field of research. Algorithms can be generally classified into one of the following two types: seek the best/efficient routing path/process. Therefore, the choice of pipelines must be able to process efficiently the flow of data that is continuously generated to bring out the best possible and optimal traffic and routing solutions that are useful for maintaining efficient air traffic flows.

Algorithms that behave “optimally” as much as possible are characterized as developments of operational research (OR) algorithms. An “optimal” solution is sometimes hard to implement, but generally, a class of good solutions can be identified using heuristics. Most of the existing TXA algorithms can be classified and divided into heuristic (rule-based) ones, statistical ones, or ones based on a combination of both approaches. Indeed, heuristic algorithms are mainly based on rule-based methodologies, while statistical approaches are based on statistical evidence-gathering mechanisms. Nowadays, due to the ICT revolution and the increase in hardware production and innovation, both approaches can be advantageously employed to provide better performance, although none of them can give a good trade-off between the optimality of the solution and computational complexity. The selection of TXA algorithms strongly depends on the three main points summarized in the list below.

A smart combination of results from different algorithms and run-time applications is essential. In addition to the traditional TXA algorithm approaches it is also possible today to develop predictive and simulation capabilities by applying artificial intelligence in general, machine learning, brain-inspired techniques, or techniques of unsupervised learning. Moreover, reinforcement and online learning methodologies are very useful for developing “self-taught” systems. Runtime adaptive sequential learning strategies using AL algorithms are useful and important for developing small, innovative intelligence within traditional heuristic and statistical control systems. In this way, OR algorithms can also be federated, and their results can be used as inputs for predicting traffic and for developing potential methods and techniques to increase network efficiency. Applications of machine learning occur in different fields, where algorithms of variable complexity are employed and “trained” based on available data for diverse purposes, starting from knowledge agreement to knowledge increase. In all these fields, the importance of algorithm choice is always very high. In particular, regarding traffic analysis, one of the main reasons for applying it is to achieve a sort of prediction with high fidelity to reproduce network spotting, which can take different parameters and can change in real time. In operations, traffic analysis is also used for addressing and assessing new flight stationery placements by purchasing important organic virtual search engine traffic. To provide services for QoS, it is also important to apply real-time assessments on traffic analysis. Each algorithm has its trade-offs, and it must be chosen depending on the final output needed.

6.5.3. System Design and Architecture

To enable the integration of AI-assisted analysis into routing architectures, several system design requirements need to be met. In addition to the input data sources and transit mechanisms within existing routing infrastructures, varied capabilities are necessary. For instance, data processing capabilities for handling raw data need to be interlinked through single or multiple processing units, and the mechanisms to make traffic management-related decisions need to be present. Moreover, efficient means of transmitting these decisions into operational routines are of importance. It is anticipated that our suggested system architecture can be somewhat generic to fit a broad spectrum of data sources, AI models, and decision mechanisms, as well as relevant system adaptation to newly adopted frameworks.

A critical issue is to guarantee that the system performs robustly under a broad spectrum of traffic situations, significantly transcending the high-level traffic management pursued, and can be developed at a scale in line with massive IoT-type routing solutions. The proposed system design and architecture can be seen with five interconnected components from data input to decision-making. These components are the AI model, data storage, data processing, topology structure, and data collection system. The AI model is used to analyze the input data. The data storage component is employed for staging multiple traffic data before AI-based analysis in the AI model component. As soon as data are being processed and analyzed in one operational state, the system can switch to another operating state while using new data.

6.6. AI-Assisted Traffic Analysis

Traffic analysis on traffic infrastructure used for today's on-demand mobility systems has been a significant part of the infrastructure itself since the early days. Originally, the technologies were limited and traffic data was processed manually or with historical data. Today, we have the infrastructure to gather, transfer, and process traffic data at high frequency in real-time. By using AI technologies, traffic data can be transformed into actionable insights on a nearly real-time basis and enable management decisions on routing infrastructure. For distributed systems and operations, traffic needs to be analyzed on a decentralized basis, limiting the guaranteed quality of the AI decisions. For each decision maker and level of decision making, the time frame for predictions and decision optimization is strictly limited and may support different frequencies from instance-based to a few times an hour decisions. Consequently, AI-supported real-time traffic analytics can have a positive impact on mobility systems in a few ways of enhancing our prediction, command, decisions, and control. What is especially promising are predictive analyses that can be applied to learning capabilities from historical traffic data. Advanced predictive algorithms are not only able to uncover complex patterns and interdependencies between different mobility data, but they can also forecast future trends and traffic conditions. Real-time travel time data are used to predict the time for busy and less busy trains. Similarly, a vehicle-sharing system uses an AI-based application to forecast the number of rentals at each car-sharing station for up to 72 hours.

6.6.1. Real-Time Data Processing

Real-Time Traffic Data Processing. Developing traffic analysis systems with real-time processing capabilities is of the utmost importance because timely congestion detection and accurate forecasting are critical to managing traffic in city environments. The more promptly changing traffic conditions can be addressed, the less impact they tend to have on overall traffic congestion levels. Real-time traffic information can be leveraged to improve decision-making concerning dynamic signal control, actively route traffic along more favorable roads, and alleviate congestion by rerouting vehicles through new paths.

Processing Algorithms. The development of big data through the use of AI-assisted computing can approach quick solutions by analyzing a large amount of data in different formats to provide timely traffic forecasting and congestion management. AI-assisted computing can extract hidden information within the dataset and provide a summary of the data to assist the transportation decision support system. Set operations can produce a large number of aggregated cell counts consisting of different types of vehicles that can represent various trips in the metropolitan area. When combined with micro-simulation, operations to add route time and calculate percentages in the cells can give a real-time prediction of congestion.

Real-Time Data Acquisition. Real-time data can be collected from sensor networks located in and around urban zones. Automated traffic signals, for example, have the capability of collecting real-time data on traffic densities in and around the surrounding urban zones. With the use of geospatial technology, environmental sensors installed on large and small transit vehicles and smartphone applications can be used to collect data and determine transportation preferences in the study areas. Mobile applications can also be designed to collect real-time passenger origin and destination data as well as time spent at transit stops. With the use of programming technology, real-time transit schedule services from static and real-time location data can be calculated. This will provide real-time pickup/drop-off schedules when prospective passengers select the service online or on a smartphone application. Services will then provide real-time matching of ride requests to the on-call and subscription riders. The response feedback is then forwarded to the passengers' mobile applications.

6.6.2. Predictive Analytics for Traffic Patterns

Traffic analysis is not always restricted to analyzing the current composition of traffic on a given infrastructure. Rather, using historical traffic data encourages traffic analysts to predict, based on forecasts of increased or decreased traffic congestion, when self-optimizing route architectures could face significant degradations in user quality of service. Conclusively, AI algorithms can predict future traffic patterns and user behaviors for proactive traffic management. They can forecast areas of the city that will see increased traffic so that the self-optimizing route can guide traffic to prevent congestion.

Predictive analytics encompasses a variety of techniques: failure prediction, forecasting, regression modeling, time series modeling, and classification. For traffic prediction from IoT data logs, the technique of forecasting is most relevant. Traffic prediction forecasting techniques have been used for many years to forecast future traffic intensity, given the traffic history situation from the past. Additional studies have shown that certain machine learning algorithms such as support vector machine, random forest, gradient tree boosting, and long short-term memory can be trained with predictive capability to accurately forecast upcoming traffic patterns. A sufficiently accurate prediction model has significant implications for getting accurate information about anticipated trends for infrastructure development. With such data, the self-optimizing route can set vehicular routes in anticipation of congestion, saving commuters time and reducing congestion on alternate routes. Overall, accurate forecasts help with proactive management in a variety of urban planning and infill development applications.

6.7. Conclusion

In this paper, we shed light on integrating traffic analysis and routing functionalities to develop more scalable and efficient traffic management solutions. We maintain that there are clear advantages of AI-assisted traffic analysis for traffic management in the future. We followed a three-step procedure to lay out our arguments. First, we found out about the relationships among AI, traffic data sources, and smart routing solutions. As a second step, we disclosed the current prestige of works combining traffic data analysis and routing solutions. In doing so, this paper aims to answer questions such as: What are these works' main goals? To what extent are these results applicable to the different processes - traffic analysis and network optimization? In the process, we draw from these essentials to examine whether similar applications can be made in other traffic-related processes.

We have drawn insight from this paper. Having initiated our study, we pondered over the potential benefits of AI-assisted traffic analysis for self-optimizing routing architectures. Second, we delved into some recent concepts concerning interconnected traffic management solutions. Based on our findings, we contend that these efforts are an excellent illustration of applied research into the role and potential of traffic data quality in overall smart transport solutions. Provided ample funding and an increased degree of traffic management and operators' support, significant improvements in the compatibility of normal and emergency traffic flows can be achieved. In terms of future research priorities, we argue that the judgment, sophistication, and support level of smart traffic management systems and operators should be the primary foci. How to guarantee the accessibility, verifiability, and interpretability of traffic data and intelligent processing outputs in various situations should be the subject of a follow-up study.

6.7.1. Implications and Future Directions

The congestive effects of traffic are not breaking news; once the roads are full, traffic comes to a stall, hindering overall throughput. The makeup of seemingly identical autonomous cars can introduce an element of chaos to these systems. In dense areas,

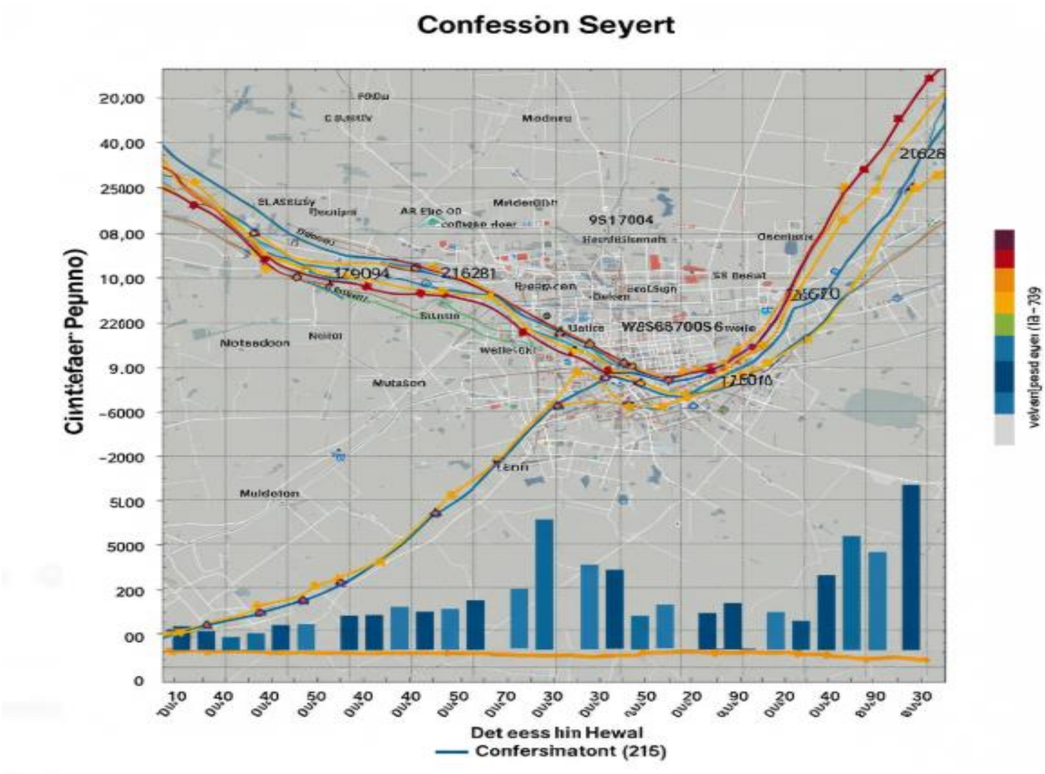

Fig 6 . 3 : Time-Series Congestion

perhaps a one-block difference in routing can compound similar delays into massive inefficiencies. Ultimately, mobility data processing should indeed be performed as an evolving and interactive function. Such a loop: model, plan, act, observe belongs to research specialties of vehicle traffic, technology, and usage for smoothing and optimization. It also embraces preferences placed on transportation modes. Algorithmic efficiency of traffic splitting and data sharing is, hence, critically important in shaping a techno-paradigm of a meaningful city.

The more routes we can construct and fill up with data, the more possibilities each of the respective agents will have. For long-term change or improvements, we firmly believe that infrastructure and governance play jointly important roles. It's worth mentioning that once we have believable analytics, various legal and legislative adjustments could emerge that would be beneficial for all the stakeholders involved. We hold strongly to the belief that a technologist, a city planner/architect, and an economist, or jurisdiction/policy maker, should productively engage and leverage such research in the future. Further issues such as data governance and security are also important to unearth.

6.7.2. Key Findings and Recommendations

Our findings are as follows. 1. When the AI suggests good threshold levels for switching traffic channels based on the analysis of traffic, the increase in convenience for prioritized traffic is significant in both operating scenarios. Furthermore, the same tendency from a decrease in small delay ratios to an increase in the largest ratio was seen in both scenarios. In the basic threshold-based operation, the travel time and the amount of traffic fluctuate largely. 2. Daily travel characteristics in time spatial diagrams that are suggested to express the frontal shapes of the distributed traffic jams were found. 3. The AI control rule outperforms the baseline threshold rule and the conventional control law. In a congestion-free regime, our control system diversely distributes the traffic by adjusting the traveling speed; in a traffic jam regime, the travel time converges to an ideal maximum speed. It is difficult to determine an optimal spatial post-distribution travel time because the conventional traffic algorithm has input and output factors. That is, in practice, it is difficult to set an appropriate bound. 4. Ninety percent of the entire traffic can turn in the right direction using the novel method.

In this manuscript, methods of AI-assisted traffic analysis for self-optimizing routing architectures were discussed. As a core aspect of the discussion, it was shown that AI-assisted traffic analysis promotes value-added services for businesses and private citizens. In light of these facts, practical implications and recommendations for the development of policies and infrastructures are suggested. In our future efforts, we will verify the practicality of the findings by studying actual traffic data. Furthermore, the effects of proposed technologies on the traffic system should be discussed, taking into account various vulnerabilities, such as delays in data reception times with moving vehicles.

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