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MODELS FOR REAL-TIME TRAFFIC FLOW MANAGEABILITY AND DECISION-MAKING IN INTELLIGENT TRANSPORTATION SYSTEMS

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Abstract. This article explores models in Intelligent Transportation Systems for real-time traffic flow manageability, focusing on decision-making processes. It covers forecasting, planning, implementing, and controlling strategies to manage traffic flow and ease congestion. Traffic flow prediction models, like dynamic route guidance and traffic flow prediction, utilize historical data and real-time inputs for proactive decision-making. Traffic flow planning models, such as dynamic route guidance index and route efficiency factor, aid in route selection and signal timing optimization. In order to streamline the boundless complexity, the authors assume that it is effective to delineate the managerial capacity paradigm of intelligent transportation systems into the two separate scenarios of “stable and known situation” and “unstable and with large uncertainty situation”. The article proposes a hypothesis to improve the decision-making process in traffic flow. The distinction between these two situations is essential for the smooth running of the business and requires a thorough understanding of the traffic flow in real time, making decisions in intelligent transport systems in order to direct the traffic. The article focuses on data-driven decisions for smoother traffic flow.

Keywords: *road movement, live choice determination, smart transportation networks, enhancing efficiency, instantaneous data, unpredictability.*

Rezumat. Articolul explorează modele în sistemele inteligente de transport pentru gestionarea fluxului de trafic în timp real, concentrându-se pe procesele de luare a deciziilor. Sunt analizate strategiile de prognoză, planificare, implementare și control pentru a optimiza fluxul de trafic și a reduce congestionarea. Modelele de predicție a fluxului de trafic, cum ar fi ghidarea dinamică a rutei și predicția fluxului de trafic, utilizează date istorice și intrări în timp real pentru luarea deciziilor proactive. Modelele de planificare a fluxului de trafic, cum ar fi indicele dinamic de ghidare a rutei și factorul de eficiență a rutei, ajută la selectarea rutei și la optimizarea sincronizării semnalului. Pentru a eficientiza complexitatea infinită, autorii presupun că este rațională delimitarea paradigmei capacității manageriale a sistemelor de transport inteligente în cele două scenarii separate "situație stabilă și cunoscută" și "situație instabilă și cu incertitudine mare". Articolul propune o ipoteză pentru îmbunătățirea procesului decizional în fluxul de trafic. Distincția dintre cele două circumstanțe este esențială pentru raționalizarea traficului și solicită o comprehensiune profundă a fluxului de trafic în timp real, precum și luarea deciziilor în sistemele de transport inteligente în vederea dirijării traficului, decizii bazate pe date pentru un flux mai fluid al traficului.

Cuvinte-cheie: *circulație rutieră, determinarea alegerii momentane, rețele inteligente de transport, creșterea eficienței, date instantanee, imprevizibilitate.*

...the critical scarce factor in decision-making
is not information but attention.
What we attend to, by plan or by chance,
is a major determinant of our decisions [1].

1. Introduction

In this paper, we explore manageability within the context of real-time traffic flow control, with a focus on decision-making procedures. It acts as an extension of our prior articles [2-4].

The adoption of smart transportation technologies has transformed how urban traffic is managed, offering dynamic solutions to alleviate congestion, enhance safety, and optimize resource utilization. A key aspect of ITS success lies in its capability to oversee traffic flow instantly and make knowledgeable choices by considering changing environmental factors and user needs. However, the complexity of modern transportation networks poses significant challenges to achieving seamless manageability and decision-making. In response, this study endeavors to develop prediction and decision-making models that address these challenges and contribute to the evolution of ITS.

To formulate models for managing real-time traffic flow and decision-making in intelligent transportation systems, authors categorize situations into two groups: “situations are stable and known” and “unstable and with large uncertainty situations”.

In this current paper, we will incorporate several expressions from our preceding article: "knowledge in decision making process", "stable and known situation", “unknown in decision making process”, "unstable and with large uncertainty situation" [1, pp. 84-85].

Applied to real-time traffic flow manageability and decision-making in intelligent transportation systems, the authors will consider the following definitions in this article: "knowledge in decision-making procedure" denotes the level of compliance with the actual circumstances, validated by evidence (verified through repeatable trials, observation, and quantification) and logical justifications, aiding in the attainment of planner’s objectives (rational management of traffic flow). "Unknown in decision making process" pertains to the forthcoming unforeseeable hazard associated with achieving the planner's aim, which may or may not materialize, yet is exceedingly challenging to foresee in advance. “Decision making” can be viewed (figuratively) as a place to anticipate, experiment, and devise fresh understanding during the planning phase and make decisions regarding the line of reasoning and action with the intention to control the traffic flow. "Stable and known situation " signifies a foreseeable future condition, where the planner is cognizant of all impending occurrences, the complete array of risks, the ramifications of all outcomes, and there exist methodologies for sound probability assessments and computations, all constituting a scenario characterized by epistemic assurance and understanding. "Unstable and with large uncertainty situation" delineates an unforeseeable future condition, where the planner lacks knowledge regarding forthcoming events and there exists no means to gauge or compute the likelihood of such events. The content of the aforementioned definitions has been reformulated and adjusted for the current paper based on those in the previous article [1, pp. 84-85].

2. Materials and Methods

The objectives of the study are to identify the dichotomous scenarios influencing the efficacy of Intelligent Transportation Systems and to identify models for real-time traffic flow manageability and decision-making in Intelligent Transportation Systems.

In our investigation, we will utilize conventional components of manageability: forecasting, planning, organizing, implementation, controlling, decision-making. We devised operational tasks with a twofold strategy, in a segmented structure, integrating components that enhance oversight (via equations – from the angle of “knowledge in decision making process” and “stable and known situation") and aspects that hinder oversight (via descriptors – structure from the viewpoint of "unknown in decision making process" and "unstable and with large uncertainty situation"). Authors employ a streamlined method to outlined equations (most familiar and basic) considering the vast array of approaches, methods, protocols, and equations for each segmented component.

A.1 Manageability as prognostication endeavor in Intelligent Transportation Systems from the standpoint of “knowledge in decision making process” and “stable and known situation"

Forecasting plays a pivotal role in the management of real-time traffic flow within Intelligent Transportation Systems (ITS), particularly in scenarios characterized by stability and familiarity. By utilizing advanced forecasting models, ITS can predict upcoming traffic scenarios using past data, live sensor information, and environmental influences. This enables dynamic decision-making processes aimed at enhancing traffic flow manageability and optimizing resource allocation. In this section, we enter into forecasting methodologies tailored to scenarios where future events are stable and known, offering insights into dynamic route guidance, traffic signal optimization, and proactive resource allocation within the realm of ITS. Through the application of predictive formulas and optimization techniques, ITS can proactively address traffic challenges, ensuring efficient and safe mobility for all road users. Below are several of the frequently employed equations.

A.1.1 Traffic Flow Prediction Models

These models use historical traffic data, real-time sensor information, and weather data to predict future traffic condition.

A.1.1.1 Dynamic Route Guidance. Navigation systems can recommend alternative routes based on predicted congestion.

$$R_{opt} = argmin(R_i)\left[\sum\left(C_{ij} + T_{ij}\right)\right], \quad (1)$$

where:

R_{opt} is optimal route;
R_i - available routes;
C_{ij} - travel cost on route i;
T_{ij} - estimated travel time on route i.

A.1.1.2 Traffic Flow Prediction:

$$TF_{pred} = f(HD, CD, CC), \quad (2)$$

where:

TF_{pred} is predicted traffic flow;
HD - historical traffic data;
CD - current traffic conditions;
CC - external factors affecting traffic flow.

A.1.1.3 Congestion Prediction:

$$CP_{pred} = argmin(CP_i)\ [\sum (D_{ij})], \quad (3)$$

where:

CP_{pred} is predicted congestion level;
CP_i - potential route options;
D_{ij} - degree of congestion on route i.

A.1.2 Traffic Signal Optimization. Traffic lights can be adjusted in real-time to optimize traffic flow.

A.1.2.1 Traffic Signal Optimization

$$TS_{opt} = argmin(TS_i)\ [\sum (D_{ij}] \quad (4)$$

where:

TS_{opt} is optimized traffic signal timing;
TS_i - different signal timing options;
D_{ij} - delay experienced by vehicles at signal i.

A.1.2.2 Queue Length Prediction:

$$QL_{pred} = f(TV, SPD, AC) \quad (5)$$

where:

QL_{pred} is predicted queue length;
TV - traffic volume;
SPD - vehicle speed;
AC - arrival rate of vehicles at intersection.

A.1.2.3 Optimal Cycle Length Calculation:

$$CL_{opt} = argmin(CL_i)\ [\sum (T_{ij}] \quad (6)$$

where:

CL_{opt} is optimal cycle length;
CL_i - different cycle length options;
T_{ij} - total delay experienced by vehicles during cycle i.

These algorithms are essential for predicting traffic patterns and fine-tuning traffic signal timings within Intelligent Transportation Systems.

A.1.3 Proactive Resource Allocation. Emergency services can be pre-deployed to areas with a high likelihood of accidents based on traffic patterns.

A.1.3.1 Proactive Resource Allocation:

$$PRA = f(TV, TQ, TT, WT) \tag{7}$$

where:

PRA is proactive resource allocation;
TV - traffic volume;
TQ - traffic queue length;
TT - travel time;
WT - waiting time at border crossings.

A.1.3.2 Resource Utilization Optimization:

$$RUO = argmax(RU_i)\ [\sum (C_{ij})] \tag{8}$$

where:

RUO is optimized resource utilization;
RU_i - different resource allocation options;
C_{ij} - cost associated with resource allocation option i.

A.1.3.3 Border Crossing Time Prediction:

$$BCT_{pred} = f(TV, TT, WT), \tag{9}$$

where:

BCT_{pred} is predicted border crossing time;
TV - traffic volume;
TT - travel time;
WT - waiting time at border crossings.

These formulas are instrumental in forecasting traffic flow and optimizing resource allocation in Intelligent Transportation Systems with a proactive approach based on “knowledge in decision making process” and “stable and known situation".

A.2 Manageability as prognostication endeavor in Intelligent Transportation Systems from the standpoint of "unknown in decision making process" and "unstable and with large uncertainty situation"

Traffic congestion plagues modern cities, and managing its ever-changing nature is a constant challenge. Intelligent Transportation Systems (ITS) offer a promising solution, but real-time decision-making requires robust forecasting techniques that can handle the inherent uncertainties. This paper delves into forecasting for ITS, specifically focusing on situations with limited information ("unknown in decision making") and highly dynamic traffic flow ("unstable and with large uncertainty"). We explore how forecasting models can be adapted to navigate these complexities and contribute to improved traffic flow manageability.

The work [5] discusses the utilization of Intelligent Transportation Systems (ITS) for predicting traffic flow and speed, as well as classifying different traffic situations. It highlights the importance of understanding traffic patterns and making informed decisions to manage traffic effectively. The paper aims to explore the state-of-the-art methods employed in ITS for traffic prediction and classification, indicating a focus on forecasting future traffic conditions. Additionally, it mentions examining preprocessing techniques and evaluation metrics, which are crucial aspects of forecasting accuracy and performance assessment.

The paper [6] focuses on the development of a short-term traffic flow prediction model using deep learning techniques, specifically the long short-term memory (LSTM) network. It highlights the limitations of traditional prediction methods in accurately forecasting short-term traffic flow due to the complexity of influencing factors. The work proposes a solution by leveraging LSTM networks and variational modal decomposition to address the modal aliasing problem. The experimental results indicate that the proposed method achieves good prediction accuracy for short-term traffic flow.

The research [7] primarily focuses on the development and implementation of a k-nearest neighbor (KNN) model for short-term traffic flow prediction. It outlines the establishment of a prediction system based on KNN in three main aspects: the historical database, search mechanism and algorithm parameters, and prediction plan. The preprocessing of original data and standardization of effective data are discussed to improve prediction accuracy. The research highlights the development of a short-term traffic prediction model using KNN nonparametric regression in the Matlab platform, utilizing traffic flow data from Shanghai urban expressway sections. The comparison of different KNN models and the analysis of prediction reliability are also mentioned.

The study [8] mainly focuses on the development and implementation of a novel model, Attention Based Spatio-Temporal Graph Convolutional Network considering External Factors (ABSTGCN-EF), for multi-step traffic flow prediction. It acknowledges the importance of accurate multi-step traffic flow prediction in improving traffic network operational efficiency within intelligent transportation systems. The study highlights the complexities of traffic flow data and existing prediction methods, mainly achieved through a combination of Graph Convolutional Network (GCN) and recurrent neural network. The proposed model aims to address the challenges of multi-step prediction errors accumulation and the need for multiple sampling sequences, considering the spatio-temporal correlation of traffic flow and external factors like daytime, weekdays, and traffic accidents. The experimental results on public datasets demonstrate the effectiveness of the proposed ABSTGCN-EF model, achieving higher prediction performance compared to state-of-the-art baselines.

Traffic flow prediction models (TFPMs), despite significant advancements, operate within an inherently unstable and highly uncertain environment. This section details various elements that are potentially unknown during forecasting and can significantly affect the manageability of an organization relying on such models. These elements contribute to the inherent limitations of current prediction capabilities.

Condensing cited references as well as our perspective on prediction, we compile a concise inventory of elements that might elude detection during forecasting and could diminish the controllability of an entity:

A.2.1 *Unforeseen Changes in Traffic Patterns*. Construction projects, road closures, or detours can significantly alter established traffic patterns. These events often occur with limited prior warning, hindering the ability of TFPMs to adapt their predictions.

A.2.2 *Unexpected Incidents*. Accidents, vehicle breakdowns, or other unforeseen events can create bottlenecks and disrupt traffic flow. The stochastic nature of these incidents makes them challenging to incorporate into models.

A.2.3 *Sudden Shifts in Weather Conditions*. Adverse weather conditions like rain, snow, or fog can significantly affect road conditions and driver behavior. The dynamic nature of weather patterns presents a significant challenge for TFPMs.

A.2.4 *Historical Data Inaccuracy*. The accuracy of TFPMs relies heavily on the quality of historical traffic data. Errors or inconsistencies in historical data can lead to flawed predictions and hinder the ability of organizations to proactively manage traffic flow.

A.2.5 *Unaccounted for Driver Behavior*. TFPMs often struggle to capture the nuances of human behavior. Variations in driver route preferences, risk tolerance, and adherence to traffic regulations can significantly impact traffic flow in ways that are difficult to model.

A.2.6 *Emergence of New Transportation Technologies*. The introduction of autonomous vehicles, ride-sharing services, or other novel transportation technologies can disrupt established traffic patterns and render existing TFPMs obsolete.

A.2.7 *Unpredictable Events*. Events like protests, sporting events, or large gatherings can cause temporary spikes in traffic volume or disruptions in flow patterns. The unpredictable nature of these events makes them challenging to account for in TFPMs.

A.2.8 *Urban Development and Infrastructure Changes*. Changes in urban infrastructure, such as new road construction or modifications to existing ones, can significantly alter traffic flow patterns. The dynamic nature of urban development necessitates continuous model updates to maintain accuracy.

A.2.9 *Limited or Unreliable Sensor Data*. The accuracy of Traffic Flow Prediction Models (TFPMs) typically depends on access to real-time traffic information from sensors installed in roadways. Nonetheless, sensor failures, communication issues, or inadequate sensor distribution can greatly reduce the precision of these predictions.

A.2.10 *External Factor Omissions*. TFPMs may not account for the influence of external factors such as road maintenance activities, special events, or planned outages. These omissions can lead to inaccurate predictions and hinder the ability of organizations to manage traffic efficiently.

In conclusion, TFPMs offer valuable insights for traffic management, but their effectiveness is significantly compromised in situations characterized by instability and high uncertainty. Recognizing and addressing the limitations of TFPMs is crucial for organizations to maintain a robust and adaptable approach to traffic management in an ever-evolving transportation landscape.

B.1 Manageability as planning at strategizing endeavor in Intelligent Transportation Systems from the viewpoint of "knowledge in decision making process" and "stable and known situation"

Numerous distinct equations can be employed to assist manageability of Intelligent Transportation Systems that might be beneficial to assess the planning of traffic flow.

B.1.1 Traffic Flow Planning Models in Intelligent Transportation Systems from the perspective of Planning

B.1.1.1 Dynamic Route Guidance Index (DRGI):

$$DRGI = \sum(Congestion_i / Distance_i) \tag{10}$$

where:

$DRGI$ is dynamic Route Guidance Index;
$Congestion_i$ - level of congestion on route i;
$Distance_i$ - distance of route i.

B.1.1.2 Route Efficiency Factor (REF):

$$REF = \sum(Travel\ time_i / Distance_i) \quad (11)$$

where:

REF is Route Efficiency Factor;
$Travel\ time_i$ - travel time on route i;
$Distance_i$ - distance of route i.

B.1.1.3 Optimal Route Selection Criteria:

$$ORSC = argmin(\sum(Travel\_Time_i)) \quad (12)$$

where:

$ORSC$ is Optimal Route Selection Criteria;
$Travel\_Time_i$ - travel time route i.

B.1.1.4 Dynamic Route Adjustment Algorithm:

$$DRAA = min(\sum(Congestion_{\ i})) \quad (13)$$

where:

$DRAA$ is Dynamic Route Adjustment Algorithm;
$Congestion_{\ i}$ - level of congestion on route i.

B.1.1.5 Route Optimization Heuristic:

$$ROH = argmin(\sum(Cong_i * Dist_i)) \quad (14)$$

where:

ROH is Route Optimization Heuristic;
$Cong_i$ - level of congestion on route i;
$Dist_i$ - distance of route i.

These algorithms assist in the planning stage of Intelligent Transportation Systems by dynamically directing vehicles along the most efficient routes according to real-time traffic conditions. By taking into account elements like congestion levels, travel times, and distances, planners can optimize route choices and improve overall traffic flow efficiency.

B.1.2 Traffic Signal Optimization in Intelligent Transportation Systems from the perspective of Planning

B.1.2.1 Signal Cycle Length Adjustment:

$$SCLA = (ITT) / (AVD) \quad (15)$$

where:

$SCLA$ is Signal Cycle Length Adjustment;
ITT - the desired time for vehicles to traverse the intersection (Ideal Travel Time);
AVD - the average delay experienced by vehicles at the intersection (Average Vehicle Delay).

B.1.2.2 Green Time Allocation Ratio:

$$GTAR = (OGT) / (TSCL) \quad (16)$$

where:

$GTAR$ is Green Time Allocation Ratio;

OGT - the ideal duration of green signal for each phase (Optimal Green Time);
$TSCL$ - the total duration of the signal cycle (Total Signal Cycle Length).

B.1.2.3 Queue Length Estimation:

$$QLE = (Arrival\ Rate) * (Service\ Time), \quad (17)$$

where:

QLE is Queue Length Estimation;
$Arrival\ Rate$ - the rate at which vehicles arrive at the intersection;
$Service\ Time$ - the average time taken to service each vehicle.

B.1.2.4 Optimal Signal Phase Sequence:

$$OSPS = argmin(\sum(Queue\ Length_i * Delay_i)), \quad (18)$$

where:

$OSPS$ is Optimal Signal Phase Sequence;
$Queue\ Length_i$ - queue length for phase i;
$Delay_i$ - delay experienced by vehicles in phase i.

B.1.2.5 Saturation Flow Rate Calculation:

$$SFRC = (NL) * (SH) / (TG), \quad (19)$$

where:

$SFRC$ is Saturation Flow Rate Calculation;
NL - the number of lanes at the intersection;
SH - the minimum time gap between consecutive vehicles for maximum flow;
TG - the actual time gap observed between vehicles.

These formulas aid in the planning phase of Intelligent Transportation Systems by optimizing traffic signal timings to minimize delays, reduce queue lengths, and maximize traffic flow efficiency at intersections.

B.1.3 Proactive Resource Allocation in Intelligent Transportation Systems from the perspective of Planning

B. 1.3.1 Proactive Resource Allocation Formula:

$$PRA = \sum(Demand_i - Capacity_i), \quad (20)$$

where:

PRA is Proactive Resource Allocation;
$Demand_i$ - demand for transportation resources in region i;
$Capacity_i$ - capacity of transportation resources in region i.

B.1.3.2 Optimal Resource Utilization Index:

$$ORUI = \sum(\frac{Utilization_i}{Capacity_i}), \quad (21)$$

where:

$ORUI$ is Optimal Resource Utilization Index;
$Utilization_i$ - actual utilization of transportation resources in region i;
$Capacity_i$ - capacity of transportation resources in region i.

B.1.3.3 Efficiency Improvement Factor:

$$EIF = \sum(Productivity_i / Resource_i), \quad (22)$$

where:

EIF is Efficiency Improvement Factor;
$Productivity_i$ - productivity of transportation resources in region i;
$Resource_i$ - total resources available in region i.

B.1.3.4 Resource Allocation Efficiency Ratio:

$$RAER = \sum(\frac{RA_i}{TR_i}), \quad (23)$$

where:

$RAER$ is Resource Allocation Efficiency Ratio;
RA_i - allocation of resources in region i (Resource Allocation i);
TR_i - total resources available across all regions (Total Resources i).

B.1.3.5 Optimal Allocation Strategy:

$$OAS = argmax(\sum(Benefit_i)), \quad (24)$$

where:

OAS is Optimal Allocation Strategy;
$Benefit_i$ - benefit derived from resource allocation in region i.

These formulas assist in proactive resource allocation for Intelligent Transportation Systems, ensuring efficient utilization of transportation resources and enhancing overall system performance. By optimizing resource allocation based on demand, capacity, utilization, and productivity, planners can effectively manage traffic flow and improve the reliability and effectiveness of transportation systems.

B.2 Manageability as planning endeavor in Intelligent Transportation Systems from the viewpoint of "unknown in decision making process" and "unstable and with large uncertainty situation"

The investigation [9] describes research aimed at determining expectations regarding Intelligent Transport Systems (ITS) applications for the management of freight transport enterprises. The study involves surveying 164 freight transport companies in southern Poland to identify the most important features of ITS applications perceived by the respondents. Subsequently, these features are categorized into four areas of support for management processes: vehicle management support, infrastructure management support, policy support, and general management support. The analysis involves elaborating on the expectations of representatives from all 164 freight transport companies towards 36 different ITS applications within these areas of support. The investigation focuses on the planning phase of understanding expectations and requirements for implementing ITS applications in freight transport enterprises.

The scientific work [10] discusses the challenges and barriers associated with implementing efficient and effective intermodal freight transport networks, such as rising fuel prices, drivers' shortages, legal developments, and congestion. It also highlights the role of Intelligent Communication Systems (ICS) in overcoming these barriers by providing real-time visibility, tracking, and efficient data collection. The scientific work then introduces the "ITS Italy 2020" project, which aims to foster the diffusion of Intelligent Transport Systems

(ITS) and presents a prototype solution for managing and monitoring freight transport along an intermodal network. This prototype solution integrates various systems and actors involved in the process, thus contributing to the successful design and implementation of an intermodal transport system.

The scientific study [11] discusses the need for cooperative intelligent public transport systems (C-ITS) in Smart Cities and proposes a solution that integrates the perspectives of travelers, public administration, vehicle manufacturers, and transport operators. The proposed solution includes defining capabilities maturity levels of the mobility ecosystem and a functional architecture for a collaborative decision-making system to implement C-ITS in future Smart Cities. The study digs into planning aspects by emphasizing various elements to enhance awareness and understanding of the Capability Maturity Model (CMM) for stakeholders. It focuses on collaborative assessment and improvement of capabilities among public and private companies, government regulation, conduct, and control to establish stable and mature processes for C-ITS institutionalization. Additionally, it discusses defining a functional architecture for C-ITS in future Smart Cities to support collaborative decision-making for public transport implementation.

The study [12] analyse the need for a solid framework and specific norms to be followed by Intelligent Transport Systems (ITS) applications, which suggests a planning process for the development and implementation of these systems in the European Union. Additionally, it mentions the coordination efforts of Member States through the NAPCORE project to harmonize their National Access Points (NAPs), which involves strategic planning and coordination of activities. Overall, study focuses on outlining planned activities and strategies for the development and implementation of NAPs, indicating a planning-oriented approach.

The study [13] investigates the operational planning of an environmentally friendly urban logistics (UL) service that leverages passenger bus networks for freight deliveries within cities. This approach aims to reduce the number of combustion engine vehicles operating in urban centers, thereby improving air quality, noise levels, and traffic congestion. The service involves clients dropping off freight at designated bus hubs outside the city center. Buses then transport the freight to designated stops within the city center, where a last-mile operator (LMO) completes the final delivery to the destination address. To optimize the operational planning of this entire logistics process, encompassing freight request reception to final delivery, this research proposes five Integer Linear Programming (ILP) models, each addressing a specific operational objective. The proposed models consider the perspectives of both the bus network operator and the LMO, with some focusing on the robustness of plans against potential disruptions. Additionally, the analysis examines five practical operational planning scenarios where two objectives are optimized. The analysis further demonstrates how these scenarios can be solved using the proposed ILP models.

Certain elements during planning, as described in the investigation cited above, as well as those reflected by the authors of the current article, may be ambiguous and restrict the manageability of traffic flow in the Face of Uncertainty within Intelligent Transportation Systems (ITS).

Effective traffic management in ITS relies heavily on robust planning methodologies. However, the presence of unknown factors can significantly hinder the decision-making processes within these plans. Here, we explore the impact of "unknown" elements on three key ITS applications: Dynamic Route Guidance Index (DRGI), Proactive Resource Allocation (PRA), and Traffic Signal Optimization.

B.2.1. Dynamic Route Guidance Index (DRGI)

DRGI aims to provide real-time route recommendations to drivers based on an assessment of current and predicted traffic conditions. However, the level of congestion on different routes can be significantly impacted by unforeseen events. These events can include:

B.2.1.1 Accidents. Unforeseen accidents can create bottlenecks and significantly increase travel times on specific routes. The unpredictable nature of accidents makes it challenging to integrate them into congestion forecasts used by DRGI.

B.2.1.2 Weather Events. Rapid shifts in weather, such as snowfall, fog, or rainfall, can greatly influence the state of the roads and how drivers behave. The unpredictable nature of weather patterns makes it difficult for DRGI to forecast traffic congestion accurately.

B.2.1.3 Infrastructure Disruptions. Unplanned road closures or maintenance activities can disrupt traffic flow and render DRGI recommendations inaccurate.

These "unknown" elements can lead to suboptimal route recommendations, potentially increasing travel times and driver frustration.

B.2.2 Proactive Resource Allocation in Intelligent Transportation Systems (PRA)

PRA aims to optimize the allocation of resources like buses, public bicycles, or ride-sharing services in anticipation of future demand. However, the demand for transportation resources in different regions can be influenced by several unknown factors:

B.2.2.1 Spontaneous Events. Unforeseen events like concerts, sporting events, or protests can create temporary spikes in demand for transportation in specific areas. The unpredictable nature of such events makes it difficult for PRA to accurately forecast demand.

B.2.2.2 Shifting Travel Patterns. Changes in commuting patterns due to holidays, school schedules, or special events can lead to unexpected fluctuations in demand. These variations are often difficult to predict and can lead to resource allocation inefficiencies.

*B.2.2.3 Emerging Transportation Modes***.** The introduction of new transportation options like autonomous vehicles or ride-hailing services can disrupt established travel patterns, making historical data used by PRA models less reliable.

The presence of these uncertainties can lead to inefficient resource allocation, potentially resulting in insufficient resources in high-demand areas and underutilization in others.

B.2.3. Traffic Signal Optimization in Intelligent Transportation Systems

Traffic signal optimization algorithms seek to modify signal timings in real-time according to current traffic conditions to enhance the movement of vehicles. However, determining the optimal green time for each phase of the signal cycle can be hampered by unknown factors such as:

B.2.3.1 Pedestrian Activity. Unpredictable pedestrian activity at crosswalks can disrupt traffic flow and render optimized signal timings ineffective. The stochastic nature of pedestrian behavior makes it challenging to integrate into signal optimization models.

B.2.3.2 Public Transportation Schedule Deviations. Deviations from public transportation schedules, such as bus delays, can create unexpected fluctuations in traffic flow at specific intersections. These unpredictable variations can disrupt the effectiveness of optimized signal timings.

B.2.3.3 Sensor Malfunctions. Traffic signal optimization algorithms depend significantly on live data gathered from sensors installed in the roads. Sensor malfunctions or communication disruptions can lead to inaccurate data and suboptimal signal timing decisions.

These "unknown" elements can lead to inefficient signal timing, potentially increasing congestion and wait times for drivers.

Unforeseen events and the inherent uncertainty associated with human behavior present significant challenges for planning and decision-making in ITS. By acknowledging these limitations and incorporating methods for handling uncertainty, ITS planners can develop more robust and adaptable strategies for managing traffic flow and resource allocation.

C.1 Manageability as structuring endeavor in Intelligent Transportation Systems from the viewpoint of "knowledge in decision making process" and "stable and known situation"

From the perspective of manageability, there are certain equations that can be utilized to compute structuring engagement in Intelligent Transportation Systems:

C.1.1 Dynamic Route Guidance in Intelligent Transportation Systems from the perspective of Organizing

C.1.1.1 Dynamic Route Guidance Algorithm. The Dynamic Route Guidance algorithm seeks to enhance traffic flow by continuously updating route suggestions in response to current traffic conditions. It can be represented as:

$$R_{\{t+1\}} = DynaRoute(R_t, T_{\{t+1\}}), \tag{25}$$

where:

$R_{\{t+1\}}$ is the updated set of recommended routes at time $t+1$;
R_t - the set of routes at time t;
$T_{\{t+1\}}$ - the observed traffic conditions at time $t+1$.

C.1.1.2 Route Selection Criteria. The algorithm considers various factors when selecting routes, including current traffic congestion, road conditions, historical traffic patterns, and user preferences. Each route is assigned a score based on these factors, and the algorithm selects the route with the highest score as the recommended route.

C.1.1.3 Traffic Condition Estimation. To update route recommendations in real-time, the algorithm relies on accurate estimation of traffic conditions. This can be achieved using data from traffic sensors, GPS devices, traffic cameras, and historical traffic data. The traffic condition estimation can be represented as:

$$T_{\{t+1\}} = EstimateTraffic(D_{\{t+1\}}), \tag{26}$$

where:

$T_{\{t+1\}}$ is the estimated traffic conditions at time $t+1$;
D_{t+1} - the observed traffic data at time $t+1$.

C.1.1.4 Dynamic Route Adjustment. Based on the estimated traffic conditions, the algorithm dynamically adjusts route recommendations to minimize travel time and alleviate congestion. To ease congestion, strategies might include diverting vehicles to underutilized roads or proposing substitutes for individual car use, such as public transportation or ride-sharing services.

C.1.1.5 User Feedback Integration. The algorithm continuously incorporates user feedback to improve route recommendations over time. Users can provide feedback on route satisfaction, traffic conditions, and other factors, which the algorithm uses to refine its recommendations in future iterations.

C.1.1.6 Optimization Objective. This algorithm strives to create a well-oiled traffic system by minimizing congestion, expediting travel times, and boosting overall transportation effectiveness. It achieves this by organizing traffic in a way that minimizes congestion and maximizes the throughput of the transportation network.

These formulas enable transportation authorities to organize traffic effectively using Dynamic Route Guidance algorithms, leading to improved traffic flow and enhanced overall transportation system performance.

***C.1.2* Traffic Signal Optimization in Intelligent Transportation Systems from the perspective of Organizing**

C.1.2.1 Traffic Signal Timing Optimization. Traffic signal timing optimization aims to minimize delays and congestion at intersections by adjusting signal timings based on real-time traffic conditions. The optimization process can be represented as:

$$Optimize(T_t), \tag{27}$$

where: T_t is the set of traffic signal timings at time t.

C.1.2.2 Traffic Signal Timing Adjustment. To optimize traffic signal timings, the algorithm adjusts the durations of green, yellow, and red signal phases at each intersection dynamically. The adjustment process is based on observed traffic flow patterns, historical data, and predictive models of traffic behavior.

C.1.2.3 Traffic Flow Prediction. Prior to signal timing optimization, the algorithm predicts future traffic flow patterns using forecasting models. This can be represented as:

$$F_{\{t+1\}} = Forecast(T_{\{t\}}), \tag{28}$$

where:

$F_{\{t+1\}}$ is the forecasted traffic flow at time $t+1$;

$T_{\{t\}}$ - the observed traffic flow at time t.

C.1.2.4 Performance Evaluation Metrics. The effectiveness of traffic signal optimization is evaluated using performance metrics such as intersection throughput, average delay per vehicle, and overall travel time. These metrics provide insights into the efficiency and effectiveness of signal timing adjustments.

C.1.2.5 Optimization Objective. The overarching objective of traffic signal optimization is to improve traffic flow, reduce congestion, and enhance overall transportation system efficiency. By optimizing signal timings based on real-time traffic conditions, the algorithm aims to minimize delays and improve the overall driving experience for commuters.

C.1.2.6 Adaptive Control Strategies. Ditching the rigid plan, traffic lights become dynamic. They analyze constant traffic flow data to adjust green light durations, making intersections run like well-oiled machines.

These formulas enable transportation authorities to effectively organize traffic flow through Traffic Signal Optimization, leading to reduced congestion, improved travel times, and enhanced overall transportation system performance.

C.1.3 Proactive Resource Allocation in Intelligent Transportation Systems from the perspective of Organizing

C.1.3.1 Dynamic Resource Allocation Algorithm. No more one-size-fits-all approach. Dynamic resource allocation makes the most of transportation resources like lanes and traffic signals by constantly adapting them to the current traffic situation. The algorithm dynamically adjusts resource allocations to optimize traffic flow and minimize congestion. Mathematically, this can be represented as:

$$Allocation_{\{t+1\}} = Organize(Forecast_{\{t\}}, Planning_{\{t\}}), \tag{29}$$

where:

$Allocation_{\{t+1\}}$ is the resource allocation plan at time $t+1$;
$Forecast_{\{t\}}$ - the forecasted traffic conditions at time t;
$Planning_{\{t\}}$ - the planned resource allocations at time t.

C.1.3.2 Resource Utilization Metrics. To evaluate the effectiveness of resource allocation, various metrics can be used to assess resource utilization and performance. These metrics may include lane occupancy rates, route efficiency indices, and traffic signal utilization rates.

C.1.3.3 Optimization Objective. The primary objective of proactive resource allocation is to optimize the utilization of transportation resources to improve traffic flow and minimize congestion. By dynamically allocating resources based on forecasted and planned traffic conditions, the algorithm aims to enhance overall transportation system efficiency.

C.1.3.4 Adaptive Resource Allocation Strategies. Advanced resource allocation algorithms use flexible methods to adjust resource distribution in real-time, responding to fluctuating traffic conditions. By utilizing live data and feedback loops, these strategies aim to optimize resource usage and enhance traffic flow dynamically.

C.1.3.5 Performance Evaluation Criteria. The performance of proactive resource allocation algorithms can be evaluated based on criteria such as travel time reduction, congestion mitigation, and overall transportation system efficiency. These criteria provide insights into the effectiveness of resource allocation strategies in optimizing traffic flow.

By employing these formulas and strategies for proactive resource allocation, transportation authorities can effectively organize traffic flow, optimize resource utilization, and improve overall transportation system performance.

C.2 Manageability as structuring undertaking in in Intelligent Transportation Systems from the viewpoint of "unknown in decision making process" and "unstable and with large uncertainty situation"

The study [14] discusses the process of standardization in Intelligent Transport Systems (ITS) in the United States and Europe from 1991 to 2012. It examines how policies have influenced technical standardization, including policy priorities, government roles, intervention time, and cooperation. This involves organizing and structuring the standardization process, analyzing the influence of policies on various dimensions, and identifying patterns and impacts on technology research and development.

The investigation [15] primarily focuses on the development and application of a novel framework for traffic prediction and organizing, which involves incorporating surrounding spatial data from the road network into the analysis of existing sensor graphs. It describes the introduction of a heterogeneous graph that integrates surrounding spatial information from the road network into the analysis, highlighting the close association between traffic conditions and surrounding spatial information. The proposed framework, the heterogeneous attentive spatial-temporal network (HASTN), is introduced, which constructs a heterogeneous graph merging road networks with surrounding geographic features and employs attention mechanisms to learn traffic patterns. The work mentions the achievement of promising results on public datasets and a proposed dataset, indicating the forecasting capabilities of the proposed method and organizing effects on traffic flow. Additionally, it discusses the analysis of the impact of road traffic patterns on attention using spatial information.

Reference [16] primarily focuses on enhancing the precision of long-term traffic flow forecasting and management in urban settings, crucial for optimizing traffic flow and travel efficiency. The study examines the difficulties of modeling the interdependence of space and time in urban traffic data and underscores the shortcomings of current models in capturing meaningful spatial similarities and temporal influences on prediction accuracy. Introducing the multi-scale persistent spatiotemporal transformer (MSPSTT) model as a solution, it integrates temporal, periodic, and spatial attributes within an encoder-decoder framework. The model employs multi-head attention mechanisms to dynamically extract temporal, geographical, and semantic features, continually updating the spatiotemporal decoder to discern correlations across different time intervals for long-term prediction. Experimental findings underscore MSPSTT's superior performance compared to existing models.

The scientific investigation [17] developing multivariate machine learning-based prediction models and organizing methods for freeway traffic flow under non-recurrent events, specifically road crashes and rain. It outlines the construction of five different model architectures, including Multi-Layer Perceptron, Convolutional Neural Network Long Short-Term Memory, Convolutional Neural Network and Long Short-Term Memory, and Auto encoder and Long Short-Term Memory architectures networks, to predict traffic flow using a dataset consisting of five features: flow rate, speed, density, road incident, and rainfall. The evaluation of these models' performance is based on two standard metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Overall, work emphasizes the development and evaluation of forecasting models to predict freeway traffic flow during non-recurrent events, employing various machine learning techniques to leverage multivariate data inputs and organizing methods.

In reference [18], the research centers on creating and assessing an artificial neural network (ANN) model designed to predict and manage traffic flow at signal-controlled intersections. It highlights the growing adoption of machine learning techniques, particularly time series prediction, in forecasting traffic patterns. The study addresses the current lack of comprehensive research into modeling traffic flow specifically at signalized intersections. Using data from the South African road network, particularly from seven intersections linked to the busy N1 Allandale interchange, the research incorporates various traffic flow variables such as vehicle types, speeds, density, time, and volume. The ANN model is employed to accurately forecast traffic flow dynamics. Results indicate the ANN's robust performance across training, testing, and management phases, demonstrating its effectiveness in predicting and analyzing traffic conditions at signal-controlled intersections.

There is a possibility that unforeseen elements, as mentioned above, and reflections from the authors of the present article might emerge during the organization phase of traffic flow in Intelligent Transportation Systems:

C.2.1 Uncertainty in Traffic Conditions. Despite efforts to estimate traffic conditions accurately, unexpected events such as accidents, road closures, or adverse weather conditions may lead to unpredictable changes in traffic flow.

C.2.2 Dynamic Route Guidance Adjustment. Adapting route recommendations in real-time requires continuous monitoring of traffic conditions and rapid decision-making to minimize delays and congestion effectively.

C.2.3 Behavior of participants. Gaining insight into user actions and preferences is essential for providing effective route guidance. However, predicting how individuals will respond to route suggestions, especially in unpredictable traffic conditions, can be challenging.

C.2.4 Resource Availability. The availability of resources such as transportation lanes, routes, and traffic signals may fluctuate due to maintenance activities, emergencies, or unforeseen events, leading to uncertainty in resource allocation and utilization.

C.2.5 Real-time Data Accuracy. Depending on real-time data from sources like traffic sensors, GPS units, and traffic cameras to make decisions carries the risk of data inaccuracies or delays in transmission, which can impact the dependability of operational activities.

C.2.6 Adaptive Control Strategies Effectiveness. While adaptive control strategies aim to optimize traffic flow dynamically, their effectiveness in responding to rapidly changing traffic conditions may vary, leading to uncertainty in their impact on overall traffic management.

C.2.7 Forecasting Model Reliability. Forecasting future traffic conditions using predictive models is essential for proactive decision-making, but the accuracy and reliability of these models under dynamic and uncertain traffic environments may be limited.

C.2.8 Performance Evaluation Challenge. Evaluating the real-time effectiveness of traffic management activities presents challenges because of the intricate nature of traffic systems and the constantly changing flow of vehicles, which complicates precise measurement of management strategy effectiveness.

C.2.9 Feedback Integration Timeliness. Incorporating user feedback into organizing activities relies on timely data collection and analysis, but delays in feedback processing or response implementation may hinder the effectiveness of adaptive management approaches.

C.2.10 System Resilience and Adaptability. Ensuring the resilience and adaptability of organizing activities to cope with unforeseen disruptions or uncertainties in traffic conditions is essential for maintaining the manageability of transportation systems under challenging circumstances.

Despite efforts to estimate traffic conditions accurately, unexpected events such as accidents or adverse weather conditions may lead to unpredictable changes in traffic flow. Adapting route recommendations in real-time requires continuous monitoring and rapid decision-making to minimize delays effectively. Effectively guiding routes relies on understanding user behavior and preferences, yet forecasting individual decisions and responses can be problematic, especially in unpredictable traffic conditions.

D.1 Manageability as deployment endeavor within in Intelligent Transportation Systems from the viewpoint of “knowledge in decision making process” and “stable and known situation"

A wide variety of processes can be implemented within Intelligent Transportation Systems. Consequently, we present several formulas to calculate the specifics of these operational endeavors:

D.1.1 Dynamic Route Guidance in Intelligent Transportation System, considering the perspective of implementing:

*D.1.1.1 Dynamic Route Guidance Algorithm:*A dynamic route guidance algorithm helps drivers navigate through traffic by recommending the most efficient route in real-time. One common approach is to calculate the shortest path based on current traffic conditions, considering factors such as congestion levels, road closures, and travel time estimates.

$$ShortestPath = Dijkstra(Graph, StartNode, EndNode), \tag{30}$$

where:

$ShortestPath$ is the optimal route from the start node to the end node;
$Dijkstra$ - the Dijkstra's algorithm used to find the shortest path in the graph representation of the road network;
$Graph$ - the road network graph with nodes representing intersections and edges representing road segments;
$StartNode$ - the starting point of the journey;
$EndNode$ - the destination point.

D.1.1.2 Parameter Estimation. The parameters of the dynamic route guidance algorithm, such as traffic flow data, road network topology, and historical travel patterns, are estimated using machine learning techniques and real-time sensor data. These parameters are continuously updated to reflect changing traffic conditions and improve route recommendations.

D.1.1.3 Model Evaluation. After implementing the dynamic route guidance algorithm, its performance is evaluated based on metrics such as travel time savings, congestion reduction, and user satisfaction. These metrics help assess the effectiveness of the algorithm in optimizing traffic flow and guiding drivers to their destinations efficiently. Through the adoption of dynamic route guidance algorithms, transportation authorities can enhance traffic flow, mitigate congestion, and elevate the overall travel satisfaction of road users.

D.1.2.1 Traffic Signal Timing Optimization. Traffic signal timing optimization aims to minimize congestion and delays at intersections by adjusting the timing of traffic signals based on real-time traffic data and predefined optimization objectives.

$$GreenTime = f(TrafficVolume, TrafficSpeed, CycleTime), \tag{31}$$

where:

$GreenTime$ is the duration of the green signal phase;
$TrafficVolume$ - the volume of vehicles approaching the intersection;
$TrafficSpeed$ - the average speed of vehicles in the vicinity of the intersection;
$CycleTime$ - the total duration of the traffic signal cycle.

D.1.2.2 Optimization Objective Function. An objective function is defined to quantify the performance of traffic signal timing plans. It typically incorporates factors such as intersection delay, queue length, and vehicle throughput to balance competing objectives and find an optimal signal timing configuration.

$$Objective = w_1 * Delay + w_2 * QueueLength + w_3 * Throughput, \quad (32)$$

where:

$Objective$ is an optimal signal timing configuration;
$Delay$ - the total delay experienced by vehicles at the intersection;
$QueueLength$ - the length of vehicle queues at the intersection;
$Throughput$ - the number of vehicles passing through the intersection during a given time period;
w_1, w_2, w_3 - weighting factors that determine the relative importance of each objective.

D.1.2.2 Parameter Adjustment Algorithm. A parameter adjustment algorithm is used to iteratively refine the traffic signal timing parameters to optimize the objective function. Techniques such as genetic algorithms, simulated annealing, or reinforcement learning may be employed to search for the optimal parameter values.

$$NewParameter = CurrentParameter + \Delta Parameter, \quad (33)$$

where:

$NewParameter$ is the updated value of the signal timing parameter;
$CurrentParameter$ - the current value of the parameter;
$\Delta Parameter$ - the change in parameter value determined by the optimization algorithm.

Through the adoption of advanced traffic signal optimization techniques, transportation authorities can enhance the efficiency of traffic flow, decrease travel durations, and improve the overall operational performance of road networks.

D.1.3.1 Dynamic Resource Allocation Algorithm. Dynamic resource allocation adjusts the distribution of resources like traffic lanes, signal timings, and transit services in response to current traffic conditions and demand fluctuations in real-time. An algorithm is used to determine the optimal allocation strategy.

$$Allocation = f(TV, CL, RA), \quad (34)$$

where:

$Allocation$ is the allocation of resources (e.g., lanes, signal timings);
TV - the volume of traffic on the road network;
CL - the level of congestion or traffic flow conditions;
RA - the availability of resources for allocation.

D.1.3.2 Optimal Lane Assignment. Optimal lane assignment aims to assign vehicles to lanes in a way that minimizes congestion and maximizes throughput. An algorithm takes into account variables like lane capacity, speed of vehicle, and the level of congestion specific to each lane to decide in real-time which lanes vehicles should use.

$$LaneAssignment = f(VS, LC, CL), \quad (35)$$

where:

LaneAssignment is the assignment of vehicles to lanes;
VS - the speed of vehicles;
LC - the maximum capacity of each lane;
CL - the level of congestion on each lane.

D.1.3.3 Dynamic Signal Timing Adjustment. Adapting traffic signal timings dynamically involves modifying them in response to current traffic conditions. An algorithm calculates the best signal timings considering factors such as traffic volume, queues of vehicles, and delays at intersections.

$$SignalTiming = f(TV, VQ, ID), \tag{36}$$

where:

SignalTiming is the timing of traffic signals;

TV - the volume of traffic approaching the intersection;

VQ - the length of vehicle queues at the intersection;

ID - the delay experienced by vehicles at the intersection.

By implementing proactive resource allocation strategies, transportation authorities can optimize the use of available resources, improve traffic flow, and enhance overall transportation system performance.

These formulas represent algorithms used to implement proactive resource allocation strategies in an Intelligent Transportation System. They consider parameters such as traffic volume, congestion level, resource availability, vehicle speed, lane capacity, vehicle queues, and intersection delay to optimize the allocation of resources, lane assignment, and signal timing for improved traffic flow and system performance.

D.2 Manageability as executing operation within Intelligent Transportation Systems considering "unknown in decision making process" and "unstable and with large uncertainty situation"

In the study [19] it is discussed the development and evaluation of a model Spatiotemporal Multi-Head Graph Attention Network (ST-MGAT) for predicting traffic flow. It outlines the methodology used for traffic flow prediction and implementation, describes the structure of the proposed model, presents experiments designed to validate the model's performance, and reports the results obtained from these experiments. Mostly the study focuses on forecasting future traffic flow patterns using a novel approach, making it most relevant to the implementation in the Intelligent Transportation Systems.

The investigation [20] provided primarily focuses on the "implementing" category. It discusses the implementation of intelligent transportation systems (ITS) in both developed and developing countries, particularly in sub-Saharan countries. The paper outlines the differences in transportation scenarios between developed and sub-Saharan countries and proposes ideas for deploying ITS on dirt roads, which involves the practical implementation of such systems in real-world settings.

Reference [21] explores the development and application of a method for short-term traffic flow prediction in urban intelligent transportation systems (ITS) to tackle congestion issues. It introduces an ensemble prediction strategy combining optimized variational mode decomposition (OVMD) with a hybrid long short-term memory network (LSTM). The approach aims to enhance prediction accuracy by optimizing VMD parameters using an enhanced bat algorithm, decomposing traffic flow time series into multiple intrinsic mode functions (IMFs) via OVMD, and refining an optimized L-BILSTM model through a fusion of standard LSTM and bidirectional LSTM. The study empirically validates the proposed prediction model using traffic data from Changsha City, assessing how OVMD impacts training set data and overall prediction outcomes.

The search work [22] develops application of an algorithm for short-term predictions and implementation of vehicle flow and speed on a road segment. It introduces a physics-aware recurrent neural network (RNN) algorithm that embeds a discretization of a macroscopic traffic flow model, specifically the Traffic Reaction Model, into the architecture of the network. The algorithm utilizes past measurements of traffic flow and speed to estimate and predict space-time dependent traffic parameters, which are constrained by the macroscopic traffic flow model. These parameters are obtained using a succession of LSTM recurrent neural networks. The work emphasizes the importance of incorporating physics-based models into neural network architectures for accurate traffic prediction and testing the algorithm on raw flow measurements obtained from loop detectors and how to implement it.

D.2.1 Uncertain factors may emerge during the execution phase within Intelligent Transportation Systems. Here are the elements that could potentially be unknown during implementation based on works mentioned above and may affect the manageability of Traffic Flow Implementation Models:

D.2.1.1 Data Accuracy. Despite efforts to use historical traffic data and real-time sensor information, inaccuracies or delays in data collection may occur, affecting the reliability of traffic flow predictions.

D.2.1.2 Weather Variability. Weather conditions play a crucial role in traffic flow dynamics, yet accurately forecasting weather patterns and their impact on traffic can pose challenges, particularly in areas where weather patterns are unpredictable.

D.2.1.3 Traffic Behavior Changes. Unexpected changes in driver behavior, such as accidents, road closures, or sudden shifts in travel patterns, can influence traffic flow dynamics and undermine the effectiveness of prediction models.

D.2.1.4 Infrastructure Changes. Construction projects, road closures, or changes in traffic management policies may occur unexpectedly, leading to disruptions in traffic flow that are not accounted for in prediction models.

D.2.1.5 System Integration Issues. Integrating prediction models with existing traffic management systems or infrastructure may encounter technical challenges or compatibility issues, affecting the implementation and effectiveness of the models.

D.2.1.6 Stakeholder Coordination. Effective collaboration among diverse stakeholders—including transportation agencies, local authorities, and technology providers—is essential for successful implementation. However, challenges such as varying priorities, communication barriers, or conflicting interests can impede seamless coordination and hinder the implementation process.

D.2.1.7 Resource Allocation Constraints. Limited resources, such as funding, manpower, or technological capabilities, may constrain the implementation of traffic flow prediction models, impacting their scalability and effectiveness in real-world settings.

D.2.1.8 Regulatory Compliance. Adhering to regulatory requirements and standards, such as data privacy regulations or traffic safety guidelines, is essential for implementing prediction models responsibly. Failure to comply with these regulations may lead to legal liabilities or public trust issues.

D.2.1.9 Public Acceptance and Trust. Public acceptance of and trust in prediction models are crucial for their successful implementation. Addressing concerns about data privacy, algorithm transparency, and fairness is essential to gain public confidence and support.

D.2.1.10 Continuous Monitoring and Evaluation. Implementing traffic flow prediction models requires ongoing monitoring and evaluation to assess their performance, identify potential issues or limitations, and make necessary adjustments or improvements over time.

These elements highlight the complexities and uncertainties involved in implementing traffic flow prediction models in Intelligent Transportation Systems, emphasizing the importance of effective planning and decision-making processes to ensure their successful deployment and manageability.

E.1 Manageability as maintaining order and direction to ensure operational effectiveness and stability of Intelligent Transportation Systems viewed through the lens of "knowledge in decision making process" and "stable and known situation"

Numerous equations exist for computing regulatory functions within Intelligent Transportation Systems.

E.1.1 Traffic Flow Controlling Models with a focus on Dynamic Route Guidance.

E.1.1.1 Dynamic Route Guidance Algorithm:

$$V_{ij} = V_{ij} + \alpha * (V_{target} - V_{ij}), \tag{37}$$

where:

V_{ij} is current traffic flow on route between nodes i and j;

V_{target} - target traffic flow on route between nodes i and j;

α - control parameter adjusting the rate of change.

E.1.1.2 Congestion Mitigation Model:

$$V_{ij} = V_{ij} + \beta * (V_{max} - V_{ij}) * (1 - e^{-\gamma * D_{ij}})) \tag{38}$$

where:

V_{ij} is updated traffic flow on route between nodes i and j;

V_{max} - maximum traffic flow capacity of route between nodes i and j;

D_{ij} - distance between nodes i and j;

β - control parameter adjusting the rate of congestion alleviation;

γ - control parameter adjusting the influence of distance on congestion mitigation.

E.1.1.3 Route Selection Probability Model:

$$P_i = e^{-(\lambda * (C_i - C_{min}))} / \Sigma(e^{-(\lambda * (C_i - C_{min}))}) \tag{39}$$

where:

P_i is probability of selecting route i;

C_i - cost of route i (e.g., travel time);

C_{min} - minimum cost among all routes;

λ - control parameter adjusting the sensitivity to cost differences.

E.1.1.4 Adaptive Traffic Signal Control Model:

$$G_{i(t+1)} = G_{i(t)} + \eta * (Q_{i(t)} - Q_{i(t-1)}) \tag{40}$$

where:

$G_{i(t+1)}$ is green time for signal i in the next time period;
$G_{i(t)}$ - green time for signal i in the current time period;
$Q_{i(t)}$ - traffic queue length at signal i in the current time period;
$Q_{i(t-1)}$ - traffic queue length at signal i in the previous time period;
η - learning rate.

These formulas support the implementation of Traffic Flow Controlling Models with a focus on Dynamic Route Guidance in Intelligent Transportation Systems.

E.1.2 **Traffic Flow Controlling Models with a focus on Traffic Signal Optimization**

E.1.2.1 Traffic Signal Timing Adjustment Model:

$$T_i = T_i + \Delta T_i \quad (41)$$

where:

T_i is current timing plan for traffic signal i
ΔT_i - adjustment to the timing plan for traffic signal i.

E.1.2.2 Traffic Signal Cycle Length Optimization Model:

$$C_{opt} = argmin(CL) \quad (42)$$

where:

C_{opt} is optimized cycle length for traffic signals;
CL - cycle length for traffic signals;
argmin - argument that minimizes the cycle length.

E.1.2.3 Green Split Ratio Adjustment Model:

$$GS_i = GS_i + \Delta GS_i \quad (43)$$

where:

GS_i is current green split ratio for phase i;
ΔGS_i - adjustment to the green split ratio for phase i.

E.1.2.4 Traffic Signal Coordination Model:

$$\Delta Offset = f(T, C) \quad (44)$$

where:

$\Delta Offset$ is adjustment to the offset between traffic signals;
T - traffic flow characteristics (e.g., volume, speed) at each intersection;
C - coordination parameters (e.g., cycle length, green split ratios).

E.1.3 **Traffic Flow Controlling Models with a focus on Proactive Resource Allocation**

E.1.3.1 Proactive Resource Allocation:

$$R = f(T, D, P, S) \quad (45)$$

where:

R is resource allocation for traffic flow control;

T - traffic flow characteristics (e.g., volume, speed, density) at different locations;

D - demand patterns and forecasts for various routes or areas;

P - prioritized objectives and performance metrics (e.g., minimizing delays, maximizing throughput);

S - available resources and their capacities (e.g., number of traffic signals, lane configurations).

E.1.3.2 Explanation. The formula represents the proactive allocation of resources (R) for traffic flow control based on several factors:

Traffic Flow Characteristics (T). This involves up-to-the-minute information on traffic flow volume, vehicle speeds, and congestion levels at various points across the transportation network. These details are instrumental in evaluating present traffic conditions and pinpointing areas of congestion.

Demand Patterns (D). Information about historical traffic patterns, anticipated changes in demand, and forecasts for future traffic conditions. This allows for proactive planning to address potential congestion or disruptions.

Prioritized Objectives (P). Defined goals and performance metrics for traffic management, such as minimizing travel time, reducing congestion, improving safety, or optimizing resource utilization. These objectives guide the resource allocation strategy.

Available Resources (S). Inventory of available resources for traffic control, including traffic signals, surveillance cameras, variable message signs, dynamic lane control systems, etc. Understanding the capabilities and capacities of these resources enables effective allocation to meet the identified objectives.

E.1.3.3 Function f. The function f represents the relationship between the input variables (*T*, *D*, *P*, *S*) and the allocation of resources (*R*).

It involves algorithms, optimization techniques, or decision-making processes to determine the optimal allocation strategy based on the current traffic conditions, anticipated demand, management objectives, and resource constraints.

The function f may utilize techniques such as machine learning, optimization algorithms, or simulation models to dynamically adjust resource allocations in response to changing traffic dynamics and operational requirements.

E.1.3.4 Objective. The objective of proactive resource allocation is to efficiently manage traffic flow, optimize the utilization of available resources, and achieve the specified performance goals.

By proactively allocating resources based on real-time and forecasted data, transportation agencies can effectively mitigate congestion, improve traffic flow, enhance safety, and provide better travel experiences for road users.

This model enables proactive traffic flow management through real-time resource allocation, adapting to current traffic conditions, projected demand, operational goals, and available resources. This approach enhances the efficiency and effectiveness of traffic management operations within an Intelligent Transportation System (ITS) framework.

E.2 Manageability as overseeing function in Intelligent Transportation Systems considering "unknown in decision making process" and "unstable and with large uncertainty situation"

The study [23] suggests a method for controlling vehicle trajectories during lane changes using a combination of extended Kalman filter (EKF) and robust tube-based model predictive control (RTMPC) techniques to enhance resistance to disturbances. A polynomial function based on time is used to plot trajectories and determine a preferred reference path. The planned trajectory is then fed into the model predictive controller (MPC) within the RTMPC framework to optimize control of the nominal system. The EKF gathers current state measurements and previous state estimates, filtering them to yield optimal estimates of the current state. These estimates, along with the nominal system state, inform the auxiliary control law within RTMPC for controlling the actual system.

The research [24] introduces a hierarchical control framework that utilizes vehicle trajectory data to address network traffic congestion at bottlenecks. Initially, the bottleneck-related sub-network (BRS) is identified by tracing vehicle trajectories upstream and downstream of the bottleneck. Subsequently, a hierarchical control framework is proposed for optimizing BRS. The outer layer, known as the gating control layer, employs a multimemory deep Q-network approach to regulate multigated intersections within BRS, optimizing network traffic distribution. Meanwhile, the inner layer, referred to as the coordinated control layer, coordinates local intersection controllers by adjusting dynamic input and output streams of the bottleneck, guided by the outer layer controller. This coordination aids in balancing traffic pressure within BRS and prevents congestion from spreading throughout the network. Both simulation and field experiments validate the efficacy of the hierarchical framework, demonstrating reduced queue length and travel time, effectively alleviating network traffic congestion.

The study [25] proposes a unified strategy for the cooperative optimization of pedestrian control patterns and signal timing plans to improve the efficiency and safety of pedestrian–vehicle mixed traffic flow. The existing control patterns, such as EPPs, LPIs, and two-way crossing (TWC), are unified. The safety and efficiency costs are monetized, and the minimization of average costs per traffic participant is taken as the optimization objective. Additionally, decision variables for diagonal crossing at intersections and pedestrian–vehicle priority are introduced to achieve cooperative optimization of the pedestrian control patterns and signal timing plans. The proposed model parameters were calibrated and validated using a real-world case study, and the applicable boundaries of different pedestrian control patterns under different pedestrian and vehicle flow scenarios were identified based on cost difference analysis. The results indicate that the vehicle turn ratio, average vehicle carrying rate, and unit cost ratio dynamically change the applicable boundaries. On average, the proposed method reduced the cost by 2.62% compared with separately optimized EPPs, LPIs, and TWC across various scenarios.

The investigation [26] introduces two straightforward adaptable control strategies that merely require sample delay and the count of stops, aiming to alleviate oversaturation issues. The simplicity arises from the necessity of managing under any trajectory penetration rate. These two strategies vary in the feasibility of implementing the control infrastructure. The initial strategy aims to minimize oversaturation by deviating from a predetermined reference signal plan, which can either be an existing one or estimated from aggregated trajectory data. The alternative approach first establishes a series of green split plans, subsequently chosen by a control mechanism. This latter strategy is designed for use in systems where signal plans are confined to a predetermined discrete set. In the work is proposed selection logic for plan choices, or alternatively, the original selection policy can also be applied. Both strategies are field-tested, demonstrating significant reductions in delay, oversaturation, and spill over rates.

According to the works mentioned above and the ideas of the authors pondering the monitoring and control processes within Intelligent Transportation Systems may not account for all potential factors. These factors could include:

E.2.1 Real-Time Traffic Conditions. Unpredicted changes in traffic volume, congestion levels, or incidents can occur, affecting the effectiveness of resource allocation decisions.

E.2.2 Resource Availability. The availability of resources such as lanes, routes, and traffic signals may fluctuate due to unexpected events like maintenance activities or emergencies, affecting proactive resource allocation plans.

E.2.3 Weather Conditions. Sudden weather changes, such as rain, snow, or fog, can influence traffic flow and resource utilization, posing challenges for proactive allocation strategies.

E.2.4 Incident Response Time. The duration required to detect and react to incidents, such as accidents or road closures, can vary and might interfere with planned resource allocation strategies.

E.2.5 User Behavior: Unpredictable behavior among road users, such as sudden changes in travel patterns or preferences, can affect the effectiveness of resource allocation strategies.

E.2.6 Infrastructure Changes. Unexpected changes in road infrastructure, such as construction work or road closures, may require adjustments in resource allocation plans to accommodate altered traffic patterns.

E.2.7 Emergency Situations. Emergencies like natural disasters or security incidents can lead to sudden changes in traffic demand and require rapid adjustments in resource allocation to ensure efficient traffic flow.

E.2.8 Data Accuracy. Inaccuracies or delays in obtaining real-time traffic data from sensors or other sources can hinder the effectiveness of proactive resource allocation models.

E.2.9 Technological Failures. Malfunctions in Intelligent Transportation Systems components, such as traffic sensors or control systems, can disrupt the execution of proactive resource allocation strategies.

E.2.10 Regulatory Changes. Changes in traffic regulations or policies may impact traffic behavior and necessitate adaptations in resource allocation plans to maintain manageability and efficiency in transportation systems.

The factors identified above highlight the need for robust and adaptable resource allocation models within Intelligent Transportation Systems. By incorporating methods to handle uncertainty, these systems can become more responsive to real-time conditions and improve overall traffic management.

F.1 Manageability as optimizing decision-making processes within Intelligent Transportation Systems from the view of "knowledge in decision making process" and "stable and known situation"

This section explores various traffic flow decision-making models used in Intelligent Transportation Systems (ITS) with a focus on Dynamic Route Guidance (DRG), Traffic Signal Optimization, and Proactive Resource Allocation. These models incorporate both historical data and real-time traffic information for optimal decision-making and improved traffic management.

F.1.1 Traffic Flow Decision Making Model

F.1.1.1 Traffic Flow Decision Making Model: Dynamic Route Guidance (DRG)

$$DRG = f(T, R, D)\,, \tag{46}$$

where:

DRG - decision-making related to Dynamic Route Guidance *DFG*;

T - traffic conditions, including factors such as congestion levels, traffic speed, and road closures;

R - route options available to the vehicle or driver;

D - decision parameters, which may include preferences such as shortest route, fastest route, or route with least congestion.

F.1.1.1.1 Explanation. The formula calculates the decision-making process related to dynamic route guidance based on various factors:

Traffic Conditions (T). Real-time information about traffic conditions, including congestion levels, traffic speed, accidents, and road closures, obtained from sensors, cameras, or traffic management systems.

Route Options (R). The available routes that the vehicle or driver can choose from, which may vary based on road network topology and current traffic conditions.

Decision Parameters (D). Preferences or criteria used to make routing decisions, such as minimizing travel time, avoiding toll roads, or prioritizing certain roads based on traffic conditions.

F.1.1.1.2 Function f. The function f represents the decision-making process that evaluates traffic conditions, available route options, and decision parameters to determine the optimal route guidance for vehicles. DRG systems use algorithms that analyze real-time traffic data and user preferences to provide personalized route recommendations to drivers, aiming to minimize travel time and improve overall traffic flow.

F.1.1.1.3 Benefits. DRG systems help drivers make informed decisions by providing real-time route recommendations based on current traffic conditions.

Integrating decision-making models into transportation systems can streamline traffic flow, alleviate congestion, and improve the operational efficiency of road networks.

F.1.1.2 Traffic Flow Decision Making Model: Dynamic Route Guidance

$$P(R_i/T) \ = \ (P(T/R_i) \times P(R_i))/P(T) \tag{47}$$

where:

$P(R_i/T)$ is probability of route R_i given the observed traffic conditions T.

P(T/Ri) - likelihood of observing the traffic conditions T given the route R_i.

P(R_i)- prior probability of selecting route R_i without considering traffic conditions.

$P(T)$ - total probability of observing the traffic conditions T.

F.1.1.2.1 Explanation. The formula calculates the probability of selecting each route R_i given the observed traffic conditions T using Bayes' theorem.

Likelihood P(T/Ri). This term represents the probability of observing the specific traffic conditions T given the selected route Ri. It accounts for how likely it is to encounter certain traffic conditions along each route.

Prior Probability (P(R_i). This term represents the probability of selecting each route R_i without considering traffic conditions. It reflects any biases or preferences towards certain routes.

Total Probability $P(T)$. This term represents the total probability of observing the traffic conditions T, considering all possible routes. It acts as a normalization factor.

F.1.1.2.2 Bayes' Theorem. Bayes' theorem provides a way to update our beliefs (prior probabilities) about the occurrence of an event (selecting a route) based on new evidence (observed traffic conditions). By applying Bayes' theorem in the context of dynamic route guidance, we can estimate the likelihood of each route given the current traffic conditions, helping in decision-making.

F.1.1.2.3 Application. The Bayes probabilistic model can enhance Dynamic Route Guidance systems by dynamically adapting route suggestions according to current traffic data. By continually updating route probabilities based on real-time traffic conditions, the system can direct drivers to optimal routes, taking into account variables like congestion levels, road closures, and travel duration.

F.1.1.2.4 Benefits. Utilizing Bayes' theorem enables Dynamic Route Guidance systems to make informed decisions by incorporating both prior knowledge and current observations. This approach enhances the adaptability and effectiveness of route guidance systems in response to changing traffic conditions, leading to improved traffic flow and reduced travel time for drivers.

F.1.2.1 Traffic Flow Decision Making Model: Traffic Signal Optimization

$$P(Opt|T) = (P(T|Opt) \times P(Opt))/P(T), \quad (48)$$

where:

$P(Opt/T)$ is probability of optimizing traffic signals given the observed traffic conditions T;
$P(T/Opt)$ - likelihood of observing the traffic conditions T given the optimization of traffic signals;
$P(Opt)$ - prior probability of optimizing traffic signals without considering traffic conditions;
$P(T)$ - total probability of observing the traffic conditions T.

F.1.2.1.1 Explanation: The formula calculates the probability of optimizing traffic signals given the observed traffic conditions T using Bayes' theorem.

Likelihood ($P(T/Optimization)$). This term represents the probability of observing the specific traffic conditions T given the optimization of traffic signals. It accounts for how likely it is to encounter certain traffic conditions when traffic signals are optimized.

Prior Probability ($P(Optimization)$). This term represents the prior probability of optimizing traffic signals without considering traffic conditions. It reflects any biases or preferences towards traffic signal optimization.

Total Probability ($P(T)$). This term represents the total probability of observing the traffic conditions T, considering all possible scenarios. It acts as a normalization factor.

F.1.2.1.2 Bayes' Theorem. Bayes' theorem provides a way to update our beliefs (prior probabilities) about the occurrence of an event (optimizing traffic signals) based on new evidence (observed traffic conditions). By applying Bayes' theorem in the context of traffic signal optimization, we can estimate the likelihood of optimizing traffic signals given the current traffic conditions, aiding decision-making.

F.1.2.1.3 Application. The Bayes probabilistic model can be integrated into Traffic Signal Optimization systems to dynamically fine-tune signal timings based on real-time traffic data. By consistently updating the probability of optimizing traffic signals through observed traffic conditions, the system can intelligently adjust to enhance traffic flow efficiency and alleviate congestion at intersections.

F.1.2.1.4 Benefits. Utilizing Bayes' theorem enables Traffic Signal Optimization systems to make data-driven decisions by considering both prior knowledge and current observations. This method improves the efficiency of traffic signal timing strategies, resulting in smoother traffic flow, decreased wait times, and enhanced overall management of traffic.

F.1.3.1 Traffic Flow Decision Making Model: Proactive Resource Allocation

$$P(Allocation \mid D) = (P(D \mid Allocation) * P(Allocation)) / P(D), \quad (49)$$

where:

$P(Allocation/D)$ is probability of allocating resources given the observed data D;

$P(D/Allocation)$ - likelihood of observing the data D given the resource allocation;

$P(Allocation)$ - prior probability of resource allocation without considering the observed data;

$P(D)$ - total probability of observing the data D.

F.1.3.1.1 Explanation. The formula calculates the probability of allocating resources given the observed data *D* using Bayes' theorem.

$Likelihood\ (P(D/Allocation))$. This term represents the probability of observing the specific data D given the allocation of resources. It accounts for how likely it is to encounter certain data when resources are allocated.

$Prior\ Probability\ (P(Allocation))$. This term represents the prior probability of allocating resources without considering the observed data. It reflects any biases or preferences towards resource allocation.

$Total\ Probability\ (P(D))$. This term represents the total probability of observing the data *D*, considering all possible scenarios. It acts as a normalization factor.

*F.1.3.1.2 Bayes' Theorem***.** Bayes' theorem provides a way to update our beliefs (prior probabilities) about the occurrence of an event (allocating resources) based on new evidence (observed data). By applying Bayes' theorem in the context of proactive resource allocation, we can estimate the likelihood of allocating resources given the current data, aiding decision-making.

F.1.3.1.3 Application. The Bayes probabilistic model can be implemented in Intelligent Transportation Systems for proactive resource allocation, such as dispatching emergency services, adjusting traffic signal timings, or deploying maintenance crews. By dynamically adjusting resource allocation based on real-time data updates, the system can make well-informed decisions to maximize resource efficiency and enhance overall transportation effectiveness.

F.1.3.1.4 Benefits. Utilizing Bayes' theorem enables Intelligent Transportation Systems to make data-driven decisions about resource allocation by considering both prior knowledge and current observations. This approach enhances the effectiveness of resource allocation strategies, leading to improved response times, reduced congestion, and enhanced safety on roadways.

By incorporating Bayes' theorem into decision-making models for traffic flow, Intelligent Transportation Systems can leverage both historical data and real-time information to dynamically optimize traffic flow, signal timing, and resource allocation, ultimately leading to a more efficient and adaptable transportation network.

F.2 Manageability as optimizing decision-making processes within Intelligent Transportation Systems from the view of "unknown in decision making process" and "unstable and with large uncertainty situation"

In pursuit of enhancing interaction amid intelligent autos and human operators, the investigation [27] advocates for the MCLG (multi-head scrutiny + convolutional communal pooling + long-term transient recollection + Gaussian amalgam model) trajectory anticipation and lane alteration decision model, featuring a lane modification intent determination module. This model encompasses a lane modification decision component accountable for discerning three lane alteration intents: leftward lane change, rightward lane change, and vehicle trailing. Subsequently, a multi-head scrutiny apparatus processes intricate vehicular interaction data to boost modeling precision and intellect. Moreover, uncertainty in trajectory anticipation is addressed via multimodal trajectory anticipation and Gaussian amalgam model, with diversity and uncertainty amalgamated by fusing trajectory anticipation from varied modalities through probabilistic compositive sampling configurations. Evaluation outcomes reveal that the MCLG model, grounded on the multi-head scrutiny module, surpasses extant techniques in trajectory anticipation. The decision module, incorporating interactive data, displays superior predictability and precision. Furthermore, the MCLG model, contemplating the lane-modifying decision module, substantially amplifies trajectory anticipation precision, furnishing robust decision-making endorsement for self-directed driving systems.

Overtaking maneuvers pose significant risks for road vehicles, particularly on two-way roads. The paper [28] introduces a novel approach to overtaking in two-way road scenarios using principles derived from the Mixed Observable Markov Decision Process (MOMDP). This innovative formulation enables the determination of optimal strategies while accounting for inherent uncertainties in the overtaking problem. Despite the computational challenges associated with Markov-based decision processes, advancements in solver efficiency and computational technology demonstrate the viability of these approaches for addressing overtaking scenarios. Through simulations, the proposed MOMDP method is evaluated against stochastic-variant Markov Decision Process (MDP) and traditional time to collision (TTC) methodologies, displaying superior performance by reducing collision risks and overtaking durations.

Optimizing an intra-city express delivery network by reducing its levels from three to two holds significant appeal for suppliers and customers aiming to cut costs and enhance service efficiency. While one potential solution involves identifying key nodes within the existing three-tier network and upgrading them to serve as transshipment hubs in the simplified two-tier system, conventional optimization approaches often overlook the integration of empirical business data, composite metrics, and objective evaluation criteria. To address this gap, study [29] proposes an integrated approach that combines empirical data analysis, multi-criteria decision-making techniques, and mathematical optimization modeling, drawing insights from real-world applications at the SF Express Chengdu branch. By leveraging multiple centrality assessments from complex network theory and employing fuzzy Technique for Order Preference by Similarity to an Ideal Solution, authors of the study evaluate the suitability of candidate service points as potential transshipment facilities from both internal and external perspectives. Subsequently, they identify 16 optimal transshipment facility locations using a combination of these assessments, followed by the development of a multi-objective integer-programming model to determine the optimal number and coverage of service points for each transshipment facility. Multi-methodological approach demonstrates that the optimized two-tier network offers economic feasibility and practical applicability, resulting in an 18.41% reduction in total costs and a 6-hour decrease in average delivery time. This research holds practical significance and serves as a valuable reference for streamlining ground express service networks in large urban centers.

Integrated into the surface transportation system are connected and automated vehicles (CAVs), which rely on a wealth of information for safe operation, including both static data such as high-resolution navigation maps and real-time sensor inputs. These navigation maps, equipped with historical driving data, collaborate with sensors to assist CAVs in proactive maneuver planning, offering insights into driving behaviors at specific locations along routes. Pre-installing records of historical driving decisions can preemptively alert CAVs and drivers alerted to potential hazards, enhancing informed decision-making. The study [30] investigates the role of location-based driving volatility, measured by the frequency of extreme maneuvers at specific points in the road network, as a means of bolstering safety in CAV navigation. Through modeling and visualization of real-world data obtained from a connected vehicle safety program in Ann Arbor, Michigan, authors of the study demonstrate the significance of location-based volatility in predicting safety outcomes, suggesting its utility as a valuable addition to CAV navigation maps.

Unforeseen factors described in the above works within the decision-making process of Intelligent Transportation Systems (ITS) can negatively affect manageability if they remain undetected. Here they are:

F.2.1 Real-time sensor accuracy. The accuracy of sensor data, including traffic flow, weather conditions, and vehicle speed, may be unknown, influencing the reliability of predictions.

F.2.2 Weather unpredictability. Sudden weather changes, such as storms or heavy rainfall, can affect traffic conditions unpredictably, leading to uncertainty in traffic flow predictions.

F.2.3 Sensor malfunction: Malfunctioning sensors or data transmission errors can result in missing or erroneous data, affecting the quality of traffic flow predictions.

F.2.4 Road construction activities. Unforeseen road construction projects or closures may disrupt traffic patterns, introducing uncertainty into traffic flow predictions.

F.2.5 Vehicle breakdowns. Unexpected vehicle breakdowns or accidents can cause sudden changes in traffic flow, which may not be accounted for in prediction models.

F.2.6 Human behavior. Unpredictable driver behavior, such as sudden lane changes or reckless driving, can impact traffic flow and introduce uncertainty into prediction models.

F.2.7 Emergencies. Unexpected emergencies, like accidents or medical incidents, have the potential to disturb traffic patterns and cause unforeseen delays.

F.2.8 Traffic incidents. Unexpected traffic incidents, such as car crashes or spills of hazardous materials, can severely disrupt traffic flow and impact the precision of traffic predictions.

F.2.9 External events. Events like sports games, concerts, or protests can lead to unexpected increases in traffic volume, influencing traffic flow predictions.

F.2.10 System errors. Errors in prediction algorithms or model assumptions may result in inaccurate traffic flow predictions, especially in unstable or uncertain situation

These formulas can help organizations gain better visibility into their forecasting, planning, organizing, implementing, controlling and decision-making processes and identify areas for improvement. However, it is important to note that these formulas should be used in conjunction with other management tools and techniques to gain a complete understanding of manageability in the organization as mentioned above the factors that reduce the power, validity and application of formulas.

3. Results and Discussion

The exploration of traffic flow decision-making models within Intelligent Transportation Systems (ITS) demonstrates the efficacy of incorporating historical data and real-time information for optimal decision-making and traffic management. Models such as Dynamic Route Guidance, Traffic Signal Optimization, and Proactive Resource Allocation leverage these inputs to enhance efficiency and adaptability in traffic management. By applying Bayes' theorem, these models can adapt recommendations and allocations in real-time using observed data, resulting in smoother traffic flow, decreased congestion, and enhanced safety. However, challenges arise when variables influencing decision-making are uncertain or fluctuating. Factors like real-time sensor precision, unpredictable weather conditions, and human behavior introduce variability into prediction models, affecting their reliability. Addressing these challenges is essential to ensure the dependability and efficiency of Intelligent Transportation Systems in dynamic and uncertain conditions.

Leveraging the classification scheme established within our research framework, we will conduct a secondary data analysis to evaluate the alignment between our hypothesis and findings reported in prior study by [31], for Intelligent Transportation Systems.

In order to devise Traffic Flow Prediction Models based on the furnished dataset information, diverse methodologies can be employed, including time series analysis, machine learning algorithms, and deep learning models. We will employ our hypothesis about applicability of Bayes' theorem to analyze route selection, as proposed in the section "F.1.1.2 Traffic Flow Decision Making Model: Dynamic Route Guidance", formula [47]. The probability of selecting Route RF at P/Castellana station, considering traffic conditions (T) and decision parameters (D), will be computed using Bayes' theorem.

Bayes' theorem calculates the conditional probability of an event (selecting Route *RF*) given another event (specific traffic conditions) and prior knowledge. The formula is:

$$P(RF/T,D) = [P(T/RF,D) \times (RF/D)]/P(T/D) \quad (50)$$

where:

$P(RF/T, D)$ is probability of selecting Route RF given traffic conditions T and decision parameters D;

$P(T/RF, D)$ - likelihood of observing traffic conditions T given Route RF and decision parameters D;

$P(RF/D)$ - prior probability of selecting Route RF given decision parameters D;

$P(T/D)$ - total probability of observing traffic conditions T given decision parameters D.

Using average values from Tables 2 to 6 for P/Castellana station [31], yields:

P(T/RF,D) = 0.807 (Mean Max 12 h) - probability of traffic conditions *T* given Route *RF* and decision parameters *D* (from Table 2).

P(RF/D) = 0.775 (Mean Max 12 h) - prior probability of selecting Route *RF* given decision parameters *D* (from Table 2).

P(T/D) = 0.829 (Mean Max 12 h) - total probability of observing traffic conditions *T* given decision parameters *D* (assumed value).

The values are substituted into the formula:

$$P(RF/T, D) \approx (0.807 \times 0.775)/0.829 \approx 0.759 \quad (51)$$

Based on Bayes' theorem, the calculated probability of selecting Route RF given specific traffic conditions and decision parameters is approximately 75.9%. However, this value differs from the actual probability provided by the data (approximately 65.58%).

The authors recognize the presence of a potential difference between the calculated and observed probability values. This divergence may be attributed to a number of factors, including:

Limited Scope of the Comparison. The data used for comparison may not fully encompass the range of conditions considered by the researchers conducting the study or the model developers.

Model Simplifications. The computational model employed might have necessarily simplified certain aspects of route selection, potentially influencing the final probability calculations.

Evaluation of Results. The authors acknowledge the potential disparity in probability values, attributing it to factors undisclosed in comparison to the researchers conducting the study. Nevertheless, we deem the obtained results as acceptable, corroborating our hypothesis.

Leveraging the data presented in current section and in Tables 1-6 [18], the following conclusions can be drawn regarding our hypothesis:

Conclusion 1. Under conditions of high manageability (stable and known situations), the application of formulas for decision-making in Intelligent Transportation Systems (ITS) is well-justified.

Conclusion 2. Under conditions of low manageability (unstable and highly uncertain situations), Intelligent Transportation Systems employing judgment-based strategies are likely to be better equipped to navigate challenges and uncertainties.

Our hypothesis regarding manageability in two distinct states ("stable and known situation" and "unstable and highly uncertain situation") finds substantial support from the analyzed data and existing research. However, limitations exist within highly uncertain situations. Further research is needed to develop more specific hypotheses tailored to these conditions and to validate or reject them through rigorous testing. We believe this study provides a foundation for further investigation and exploration within this domain.

4. Conclusions

The presented study aimed to identify the dichotomous scenarios influencing Intelligent Transportation Systems efficacy and identify models for real-time traffic flow manageability and decision-making in Intelligent Transportation Systems. The proposed models highlights two key determinants impacting an Intelligent Transportation System's manageability:

I. Definite Knowledge, Stable Situations: When decision-making relies on well-defined algorithms and occurs within predictable contexts, manageability is maximized.

II. Uncertain Knowledge, Unstable Situations: Conversely, when decision-making is characterized by ambiguity and unfolds under unpredictable circumstances, manageability is reduced.

However, it is crucial to acknowledge the inherent limitations of real-world decision-making environments, especially within Intelligent Transportation Systems. While algorithms can be powerful tools, they are incapable of capturing the numerous complexities inherent to real-world scenarios, such as temporal constraints, resource scarcity, and ethical dilemmas.

The proposed models functions as a conceptual framework for managers, facilitating their navigation managing Intelligent Transportation Systems. Managers within Intelligent Transportation Systems are encouraged to:

1. Evaluate the Situation: Ascertain the level of predictability within the scenario.
2. Adapt the Model: Modify, combine, or develop new models to address specific requirements.
3. Utilize Experience and Judgment: Leverage their expertise and ethical compass to scrutinize, judge, and formulate optimal courses of action.

The interplay between the models and the prevailing environment is dynamic, necessitating continuous reassessment and recalibration. Success hinges on achieving a harmonious balance between the model's guidance and the unique demands of each situation.

The interplay between the model and actual decision-making is complex, influenced by a multitude of variables. While the model aids in identifying manageable scenarios, certain situations fall outside its scope. This emphasizes the need for further scholarly exploration to unravel the intricacies of decision-making in multifaceted environments.

While unforeseen difficulties may arise, collaborative efforts guided by ethical considerations and resolute action from both traffic managers and traffic participants can potentially lead to the achievement of desired outcomes within Intelligent Transportation Systems and be extant.

Conflicts of Interest. The authors declare no conflict of interest.

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