A Dynamic Traffic Management System for Itinerary Optimization

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Abstract: Freight transport is a fundamental pillar of the European economy, accounting for more than 9 % of the European Union's Gross Domestic Product (GDP). Seaports are critical nodes in this logistics chain, handling more than 67.8% of freight transport in tonne-kilometres. This article presents an intelligent traffic management system designed specifically for road access to the Port of Rotterdam, the largest and busiest port in Europe, with the aim of optimising the flow of vehicles, improving operational efficiency and reducing CO_2 emissions.

1 INTRODUCTION

Freight transportation is an essential pillar of the European economy, contributing over 9% of the Gross Domestic Product (GDP) of the European Union (Commission, 2023). The importance of this activity lies not only in its economic contribution but also in its ability to ensure the continuous supply of essential products across Europe. Maritime harbours, which handle 67.8% of freight transport in tonne-kilometers, play a crucial role in this logistics chain (Agency, 2023).

Among these, the Port of Rotterdam stands out as the largest and busiest in Europe, managing a volume of 438.8 million tonnes in 2023 (Authority, 2023). This harbour is not only a key point for the Netherlands but also for the rest of Europe, where the goods where goods arriving in Rotterdam are distributed to cities such as Paris, Brussels, and Düsseldorf as shown in Figure 1 the Figure 1 (Logistics, 2023). However, road traffic accessing these ports faces significant challenges, such as congestion and traffic incidents, which can result in substantial economic losses for transport companies.

Leveraging advances in Information and Communication Technologies (ICT), this paper presents the work developed in the project "Development of a dashboard for the intelligent management of accesses to the port of Rotterdam" and is part of the Final Degree Project (TFG) carried out by Iván Monzón Catalán during his stay at Van den Berg ICT & ITS consultancy S.L. (Monzón Catalán, 2024). The paper details the architecture, implementation, and results of an intelligent traffic management system designed for road traffic at the Port of Rotterdam accesses. By utilizing public real-time traffic data, the system identifies congestion, detects incidents, and recommends optimal itineraries between two points. This approach not only improves travel times and reduces CO_2 emissions (International, 2023), but also highlights the potential for adopting such systems in areas where avoiding congestion due to high usage demand is critical.

Figure 1: Map with the distances to the cities where most of the goods are distributed from the Port of Rotterdam.

The structure of this paper is organized as follows: Section II presents the state of the art, providing an overview of relevant technologies and methodologies. Section III details the comprehensive analysis conducted to identify and define the requirements for system implementation. Section IV explains the ar-

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chitecture and components of the system, describing their interactions. Section V focuses on the implementation, explaining how the proposed design was realized in practice. Section VI discusses the algorithm evaluation to ensure the functionality, reliability, and performance of the developed system. Finally, Section VII presents the conclusions, summarizing the main findings and potential directions for future work.

2 STATE OF THE ART

Public data sets play an essential role in traffic management systems, offering reliable and standardized information for large-scale analysis. The European Union has established a legal framework that promotes the reuse of public sector information, recognizing its potential to boost the economy and innovation. Directive (EU) 2019/1024 on open data and the re-use of public sector information requires Member States to provide access to data, such as geographical, cadastral, statistical, or legal information, in open and machine-readable formats, ensuring its accessibility and re-use (eu-, 2019).

In the area of traffic, the European Union has implemented specific measures to ensure the availability of essential data. Commission Delegated Regulation (EU) 2015/962 requires Member States to improve the accessibility, exchange, and updating of road and traffic infrastructure data necessary for the provision of real-time traffic information services across the Union (eu-, 2015).

To centralise and facilitate access to this information, National Access Points (NAPs) have been created. The NAPs collect data provided by the traffic management entities of the national territory, including road authorities, infrastructure operators and service providers (nap, 2016). One notable example is the Dutch National Data Warehouse (NDW), which aggregates data from traffic sensors, cameras, and monitoring stations throughout the Netherlands. NDW datasets, standardized under frameworks like Data Exange V2 (DATEX II), ensure consistency and reliability, providing critical inputs for real-time and historical traffic analysis (II, 2019). These data are particularly valuable for public systems focused on large-scale traffic planning and management.

DATEX II, a standard for traffic information exchange throughout Europe, provides a unified language for traffic systems, ensuring interoperability among diverse platforms. By integrating real-time data from multiple sources, such as sensors and monitoring centers, DATEX II facilitates robust solutions for incident detection, congestion monitoring, and itinerary optimization (for Standardization, 2019). Its adaptability has made it essential for the management of urban and interurban traffic.

On the other hand, private companies such as Google, Apple, and Waze have developed proprietary systems that focus on real-time navigation and traffic updates. These platforms rely heavily on their own data ecosystems, including user-generated reports, satellite imagery, and historical traffic patterns obtained through their users. For example, Waze leverages community input to identify incidents, while Google Maps combines live traffic data with predictive algorithms to recommend the optimal itinerary (Inc., 2022). However, these proprietary systems are often optimized for commercial goals, and their datasets may not align with the regulated and validated information provided by public authorities. This divergence can result in quality discrepancies, particularly in regions where public data sets are more comprehensive (Smith and Taylor, 2021).

Private platforms excel at leveraging hyperlocalized data, thanks to their widespread user bases and advanced algorithms. Google Maps, for instance, integrates real-time movement data from millions of users to predict congestion patterns, while Waze incorporates live incident reports to improve accuracy. These approaches provide highly detailed traffic information, particularly in urban environments with high user engagement. However, their dependence on decentralized user contributions and historical traffic data introduces limitations in high-demand, dynamically changing environments such as logistics hubs or port access roads.

One of the main weaknesses of private navigation systems is their limited ability to optimize traffic flow on a network-wide scale. These systems prioritize individual travel-time minimization, often leading to suboptimal congestion management. A common issue is the re-routing of vehicles to alternative roads without considering their overall traffic absorption capacity, which can unintentionally generate new congestion points rather than alleviating existing ones. Moreover, since these systems are primarily based on reactive mechanisms, their response time to unforeseen disruptions, such as accidents or sudden road closures, is inherently delayed, making them less suitable for critical infrastructure management (Jalota et al., 2021). Bridging the gap between these two paradigms remains a significant challenge. The integration of public standards like DATEX II and NDW with the rich, dynamic data sets of private platforms offers the potential to create more accurate and scalable traffic management solutions (Brown and Jones, 2023).

The proposed system builds on this state of the art by integrating NDW real-time data with dynamic itinerary optimization tools. Unlike systems focused on predictive modeling, this approach generates itineraries based on the current state of traffic, dynamically adapting to changes in traffic conditions. By leveraging NDW's validated data and real-time inputs, the system ensures that itineraries are continually optimized for efficiency and reliability. This hybrid approach addresses the limitations of existing systems, offering a robust solution for dynamic traffic management in complex environments such as the Rotterdam harbour.

3 SYSTEM ANALYSIS

The analysis phase serves as the foundation for the development of the proposed intelligent traffic management system. This phase thoroughly examines the problem domain, system requirements, and traffic data sources to ensure technical and contextual robustness. Taking advantage of heterogeneous data sources, adhering to established standards such as DATEX II, and integrating geospatial information systems (GIS), this phase lays the groundwork for a comprehensive and efficient system.

In this analysis is to identify the functional and non-functional requirements of the system, assess the quality and usability of the traffic data, and define the data models necessary for seamless integration and processing. Furthermore, this section examines the challenges of managing real-time traffic information, ensuring compatibility with existing infrastructure, and optimizing performance for real-world application.

3.1 Functional Requirements Analysis

The functional requirements for the intelligent traffic management system were defined to ensure alignment with operational objectives and user needs. These requirements focus on providing real-time traffic visualization, optimal itinerary calculation, and seamless integration of traffic data from various sources.

The analysis identified key system interactions and functionalities, emphasizing modularity and scalability. Core use cases were defined, including the retrieval of real-time traffic data, visualization of road conditions, and generation of traffic reports. These functionalities are designed to enhance decision-making processes for traffic management and improve the user experience.

To ensure completeness and reliability, each requirement was validated against practical scenarios, considering both end-user interactions and system performance. The analysis also accounted for potential challenges such as data heterogeneity and the need for real-time updates, forming the basis for the subsequent design and implementation phases.

3.2 Data Sources and Integration into Database Tables

The company currently uses PostgreSQL as its Database Management System (DBMS), with the PostGIS extension for handling geographic data. The database already contains tables with information about the segments that make up the road network. To enhance the system, it was necessary to incorporate additional data related to traffic measurements, such as speed, traffic flow, and traffic incidents.

NDW provides real-time data files that contain critical traffic information, including traffic flow, speeds, and incident details. These files are essential for understanding the state of the road network and for enabling dynamic data analysis. The NDW files include geospatial data about detectors, road segments, and measurements taken at specific points in time.

To adapt the database to handle this new information, an extension of the existing schema was designed. Several new tables were created to integrate both static metadata and dynamic real-time measurements. This adaptation ensures efficient storage, processing, and analysis of the data. Below is a description of the key files provided by NDW and how they were mapped to the database tables:

- **Incidents Table:** Data from the *incidents.xml* files provided by NDW were mapped to this table. Fields include incident ID, type, severity, geographic location, and timestamps. This allows for the real-time tracking and analysis of disruptions within the road network.
- **Detector Table:** Metadata about the detectors, derived from NDW geospatial files, was stored in this table. Key fields include detector ID, geolocation, and associated road segment. This ensures accurate linkage between detectors and the corresponding parts of the network.
- **Real Data Table:** Traffic speed and traffic flow measurements, extracted from the *trafficSpeed.xml* files, were mapped to this table. Fields include speed, traffic flow, timestamps, and detector IDs. This table supports both real-time data analysis and historical data retrieval.

- **Measurement Characteristics Table:** Specific details about lanes and vehicle categories, included in the NDW traffic speed files, were stored in this table. These fields enable a detailed and granular analysis of traffic conditions, segmented by lane and vehicle type, providing deeper insights into network performance.

3.3 Web Services Requirements

A set of Web Services have been designed in order to feed the system with real-time data from external sources and ensure seamless integration with the database.

The main requirements for the web services were defined based on their functional roles:

- **Data Acquisition:** The services must retrieve semi-structured XML files from external sources such as the Dutch National Data Warehouse (NDW). These files include traffic flow, speed, and incident data.
- **Data Validation:** The services must validate the data in compliance with the UNE 199152-1:2016 standard (de Normalización (UNE), 2016), which establishes guidelines for data quality and analysis for interurban traffic. This ensures that the web services align with established best practices for traffic data management and processing.
- **Data Transformation:** Ensuring compatibility between the raw data formats and the relational database schema, including parsing and preprocessing steps to handle heterogeneous and large datasets.

Several challenges were identified in processing and integrating large, complex XML files:

- The heterogeneity of data structures in different files required flexible parsing mechanisms.
- The need to maintain compliance with DATEX II standards while ensuring efficient data transformations for storage in a GIS-enabled relational database.
- Handling real-time updates without compromising data integrity or response times.

Additionally, the structure of the web services was designed to ensure modularity and reliability. The services are structured to function as independent modules for data retrieval, preprocessing, and distribution, reducing interdependencies and facilitating easier maintenance in the event that the data transmission standard or validation standards are changed.

4 ARCHITECTURE DESIGN

The system is structured into four main components: web services, database, API, and front-end as shown in Figure 2. These components were designed to work cohesively, enabling seamless integration of data processing, storage, and visualization.

4.1 Architecture Components

- **Web Services:** Responsible for acquiring, processing, and inserting data into the database. These services periodically download traffic data from the NDW server, process the data to meet system requirements and insert the data in the database.
- **Database:** A relational database extended with GIS capabilities using PostGIS. It stores both static data, such as road networks and detector locations, and dynamic traffic data, such as speed and traffic flow measurements.
- **Application Programming Interface (API):** The core of the system's business logic. This component retrieves data from the database, performs necessary computations (e.g., optimal itinerary calculation), and communicates with the front-end to deliver results in real-time.
- **Front-End:** The user interface of the system. This component visualizes real-time traffic data, facilitates user interaction, and provides intuitive access to features such as itinerary optimization and traffic analytics.

4.2 Algorithm Design

The system implements a custom A* algorithm to calculate optimal itineraries based on the current state of traffic. This algorithm dynamically evaluates each segment of the road network, considering both the current traffic flow retrieved from the database relative to the maximum flow and the adjusted speed based on the Highway Capacity Manual (HCM) (Board, 2020). A weighted cost function combines these factors, ensuring that the chosen itinerary minimizes congestion while maximizing efficiency.

4.2.1 Weighted Cost Function

The cost of traversing a road segment is determined by a weighted combination of two factors:

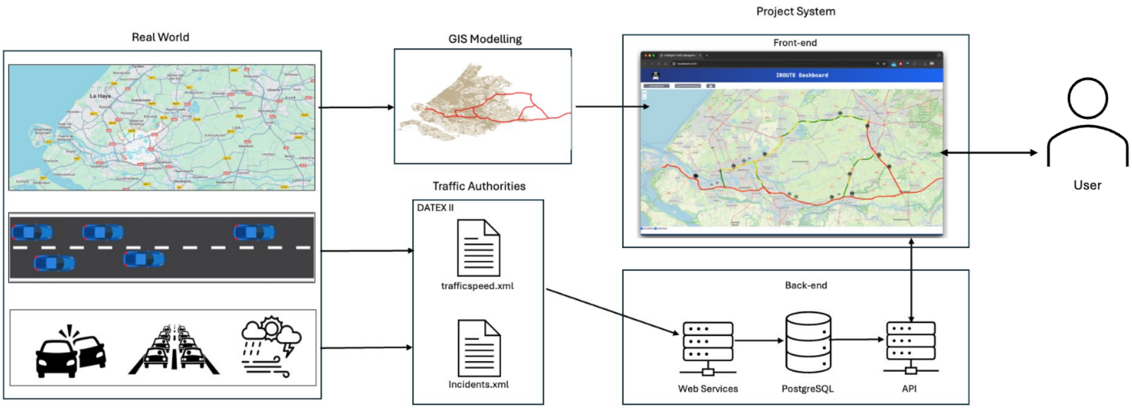

Figure 2: System architecture and external relations.

1. **Traffic Flow Factor:** Represents the congestion level of the segment, calculated as the ratio of the current flow (F_{current}) to the maximum allowable flow ($F_{\max}$):

$$\text{Flow Factor} = \frac{F_{\text{current}}}{F_{\max}} \tag{1}$$

2. **Adjusted Speed Factor:** Represents the efficiency of traveling through the segment, calculated using the HCM-adjusted speed model. The adjusted speed (V_{adjusted}) is given by:

$$V_{\text{adjusted}} = V_{\max} \cdot \left(1 - \left(\frac{F_{\text{current}}}{F_{\max}}\right)^n\right) \tag{2}$$

where:

- $V_{\max}$: Maximum allowed speed for the segment.
- $F_{\text{current}}/F_{\max}$: traffic-flow-to-capacity ratio.
- n: Empirical parameter, with a typical value of $n = 4$ for interurban roads, reflecting the non-linear impact of congestion on speed.

The speed factor is then calculated as:

$$\text{Speed Factor} = \frac{V_{\max}}{V_{\text{adjusted}}} \tag{3}$$

The total cost (C_{segment}) of a road segment is given by the weighted sum:

$$C_{\text{segment}} = \alpha \cdot \frac{F_{\text{current}}}{F_{\max}} + \beta \cdot \frac{V_{\max}}{V_{\text{adjusted}}} \tag{4}$$

where α and β are the weights assigned to the traffic flow and speed factors, respectively, and $\alpha + \beta = 1$. These weights allow for tuning the algorithm to prioritize congestion reduction or travel speed, depending on the application scenario. For this system, the weights were set to $\alpha = 0.6$ and $\beta = 0.4$, prioritizing the traffic flow factor while still accounting for the impact of the adjusted speed. This balance reflects the system's goal of reducing congestion during the itinerary optimization.

4.2.2 Algorithm Workflow

The A* algorithm calculates the optimal itinerary by minimizing the total cost from the starting node to the destination node. The heuristic function ($h(n)$) estimates the remaining cost to the destination based on the distance and the maximum allowed speed:

$$h(n) = \frac{\text{Distance to Destination}}{V_{\max}} \tag{5}$$

The overall cost function evaluated by the algorithm is:

$$f(n) = g(n) + h(n) \tag{6}$$

where:

- $g(n)$: The accumulated cost from the starting node to the current node, calculated using the weighted cost function (Equation 4).
- $h(n)$: The heuristic estimate of the cost to reach the destination (Equation 5).

5 IMPLEMENTATION

The system implementation followed the specifications outlined in the analysis and design sections, ensuring that each component adhered to the established requirements and functionality. For the API, Node.js was chosen due to its scalability and efficiency in handling asynchronous operations such as retrieving data from the database or calculating the optimal route. The database layer was built using PostgreSQL enhanced with the PostGIS extension, which supports geospatial queries. The front-end was developed using Angular with TypeScript, which allows for a modular, component-based architecture that is easy to maintain in case you want to add functionality to enhance the platform. For styling, we used Tailwind, a framework that facilitates styling essential components such as menus and modal windows.

The system was designed for exclusive desktop use, considering the expected interaction patterns and the need for large-scale data visualization. This decision was based on the anticipated usage patterns and the complexities associated with large data visualization, which were more effectively managed on larger screens.

Figure 3 shows the desktop version of the initial window with the interactive map showing the location of the loops providing the data and the segments of the road network worked.

Figure 4 shows the modal window for querying historical data for a selected loop. In this case, it shows the traffic flow.

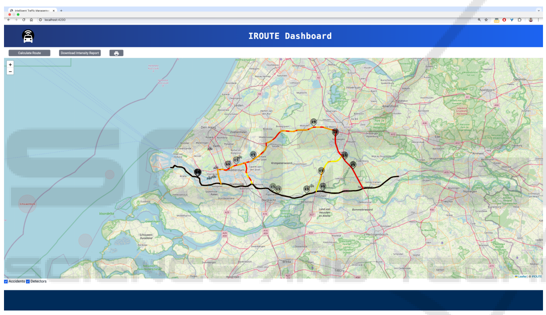

Figure 3: Graphical desktop interface of the system showing the real-time flow load with respect to its maximum capacity flow of each segment of the traffic network worked and the loops on which the data can be viewed.

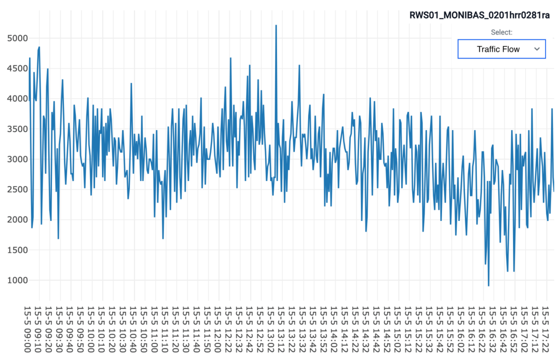

Figure 4: Graphical desktop interface of the modal displaying the traffic flow data of a loop.

6 ALGORITHM EVALUATION

To ensure the accuracy and efficiency of the proposed system, a series of tests were conducted using a simulated interurban road network. This network represents a small-scale scenario, totaling 27 km of interconnected roads. The network, shown in Figure 5, was integrated into the backend, where the algorithm was executed under various traffic conditions and compared with the classical approach.

In Figure 5, the network segments are characterized by the following attributes:

- **Smax:** The maximum allowable speed on each segment (km/h).
- **Sact:** The actual speed at which vehicles travel on each segment, reflecting real-time traffic conditions (km/h). This value is only used in the realistic scenario with traffic congestion.
- **F:** The current flow relative to the maximum flow the segment can tolerate, as per the Highway Capacity Manual (vehicles over the segment's length in one hour).
- **L:** The length of the segment (km).

The classical algorithm calculates the optimal itinerary based on the shortest travel time under ideal conditions, assuming no congestion and maximum allowable speeds ($Sact = Smax$). In contrast, the proposed algorithm dynamically evaluates the optimal itinerary by incorporating real-time traffic conditions, including speed reductions ($Sact < Smax$) and congestion levels ($F_{\text{current}} \to F_{\max}$).

The validation process assessed the system's ability to determine optimal itineraries under both ideal and realistic conditions. Verification involved testing the algorithm's adaptability to various configurations of weights (α, β) and scenarios, such as free-flowing traffic and high congestion.

The results of these tests are presented in the following subsections.

6.1 Off-Peak Test

This scenario considers optimal traffic conditions, where the current speed equals the maximum allowable speed ($V_{\text{actual}} = V_{\max}$), and the current flow is minimal, representing 10% of the maximum capacity ($F_{\text{current}} = 0.1 \cdot F_{\max}$) for all segments. Under these conditions, congestion is negligible, and travel times depend purely on the distance and maximum speed of each segment.

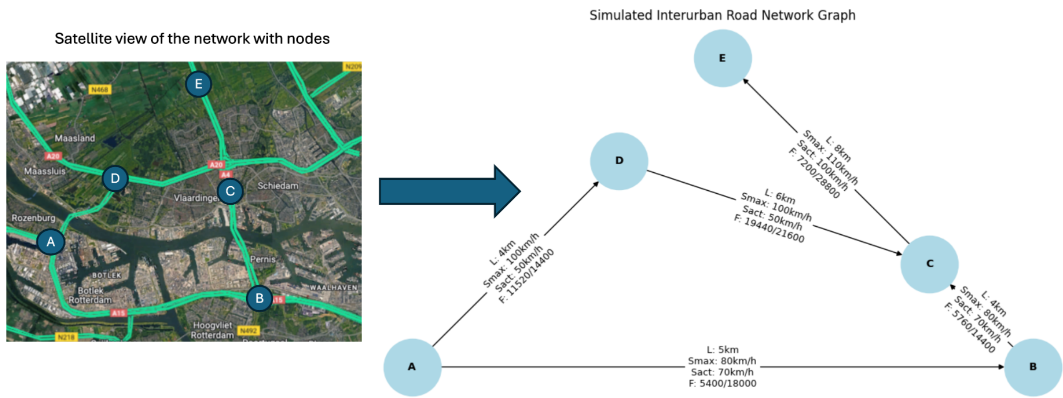

Figure 5: Real road network and simulated road network with segment attributes. Each segment is characterized by its length (**L**), maximum speed (**Smax**), current speed (**Sact**), and current/maximum flow (**F**).

6.1.1 Travel Time Calculations

In this scenario, the travel times were calculated using the following methods:

1. **Classical Calculation:**

$$C_{\text{classical}} = \frac{L}{V_{\max}} \cdot 60 \quad \text{(minutes)} \tag{7}$$

2. **Proposed Algorithm:**

$$C_{\text{segment}} = \alpha \cdot \frac{F_{\text{current}}}{F_{\max}} + \beta \cdot \frac{L}{V_{\text{actual}}} \cdot 60 \quad \text{(minutes)} \tag{8}$$

For $\alpha = 0.5$, $\beta = 0.5$, $F_{\text{current}} = 0.1 \cdot F_{\max}$, and $V_{\text{actual}} = V_{\max}$, the weighted cost simplifies to:

$$C_{\text{segment}} = 0.05 + 0.5 \cdot \frac{L}{V_{\max}} \cdot 60 \tag{9}$$

The results confirm that both methods yield identical travel times under these conditions, as shown in Tables 1 and 2.

Table 1: Travel costs under free traffic conditions (Segment-level results). Used units are: km for distance, km/h for speed and veh/h for traffic flow and minutes for time periods.

Segment	Length	$V_{\max}$	V_{actual}	$F_{\max}$	F_{current}	C_{segment}
$A \to B$	5	80	80	18,000	1,800	3.75
$B \to C$	4	80	80	14,400	1,440	3.0
$C \to E$	8	110	110	28,800	2,880	4.36
$A \to D$	4	100	100	14,400	1,440	2.4
$D \to C$	6	100	100	21,600	2,160	3.6

Table 2: Path travel times under free traffic conditions.

Path	Classical Time (min)	Algorithm Time (min)
$A \to B \to C \to E$	11.11	11.11
$A \to D \to C \to E$	9.6	9.6

6.2 Peak Hour Test

This case simulates traffic conditions with significant congestion and reduced travel speeds. In this scenario, $V_{\text{actual}} < Speed_{\max}$, and $F_{\text{current}} \to F_{\max}$ using the data which is represented at the graph edges of the Figure 5.

At tables 3 and 4 can be seen the results using the equation 7 for the classical calculation and 2, 3 for the proposed algorithm.

6.2.1 Travel Time Calculations

Table 3: Travel costs in peak hours (Segment-level results). Used units are: km for distance, km/h for speed and veh/h for traffic flow and minutes for time periods.

Segment	Length	$V_{\max}$	V_{adjusted}	$F_{\max}$	F_{current}	C_{segment}
$A \to B$	5	80	56.32	18000	5400	5.85
$B \to C$	4	80	51.2	14400	5760	6.57
$C \to E$	8	110	88.0	28800	7200	5.45
$A \to D$	4	100	45.76	14400	8640	7.58
$D \to C$	6	100	38.4	21600	10800	10.36

Table 4: Path travel times under realistic traffic conditions.

Path	Classical Time (min)	Algorithm Time (min)
$A \to B \to C \to E$	14.56	17.87
$A \to D \to C \to E$	14.18	23.39

In this peak hour case, the proposed algorithm selects $A \to B \to C \to E$ as the optimal route due to its ability to dynamically penalize segments with high congestion and low speeds. In contrast, the classical approach fails to account for congestion, selecting the shorter path $A \to D \to C \to E$. These results demonstrate the algorithm's adaptability taking into account real-worls conditions such as congestions.

7 CONCLUSIONS

The development and implementation of the proposed traffic management system have demonstrated its capability to dynamically optimize itineraries based on real-time traffic conditions. By integrating public datasets, such as those provided by the Dutch National Data Warehouse (NDW), with advanced computational algorithms like the custom A* algorithm, the system effectively addresses modern traffic management challenges. The results validate the system's ability to adapt to varying traffic scenarios, ensuring accurate, efficient, and adaptive routing solutions.

A key innovation of this project lies in the use of a weighted cost function that incorporates both congestion levels and adjusted speed factors, enabling the system to outperform classical approaches in realistic traffic conditions. The algorithm dynamically selects the most efficient itineraries, even under significant congestion, highlighting its potential for real-world applications in high-demand environments such as ports and interurban traffic networks.

Looking ahead, the next phase of development will focus on incorporating predictive capabilities through machine learning models, particularly neural networks, to forecast traffic conditions. This enhancement will enable the system to anticipate traffic fluctuations and incorporate forecasts into route optimization. By combining real-time data with predictive analytics, the system can enhance its reliability and accuracy, offering a more comprehensive tool for managing dynamic traffic conditions.

This combination of real-time optimization and predictive modelling positions the system as a cutting-edge solution in the field of intelligent transportation systems. Beyond its current capabilities, these enhancements pave the way for smarter, more sustainable traffic management strategies, addressing the growing need for efficiency and environmental responsibility in high-demand traffic networks.

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