Transportation Engineering 21 (2025) 100381

Contents lists available at ScienceDirect

Transportation Engineering

journal homepage: www.sciencedirect.com/journal/transportation-engineering

On minimizing the impact on traffic of maintenance work zones in a highway network

Mohammad Abbasi [a], Muhammad Tabish Bilal [a], Alice Consilvio [a,*], Davide Giglio [a], Nicola Sacco [a], Paula Lopez Arevalo [b]

[a] University of Genoa, Via Montallegro 1, Genoa 16145, Italy
[b] CEMOSA, Calle Benaque 9, Malaga, 29004, Spain

ARTICLE INFO

Keywords:
Highway traffic flow simulation
Road maintenance impact mitigation
Highway work zone management
Pavement status evaluation

ABSTRACT

Road maintenance plays a key role in increasing the reliability of highway networks. However, the presence of work zones hinders smooth traffic flow thus causing a temporary capacity reduction, with different impacts on traffic conditions according to the number of closed lanes or traffic deviation measures.

This research is aimed at evaluating the optimal strategy for pavement work zone management to minimize the impact on traffic and road users, increasing, at the same time, the efficiency of maintenance planning.

A three-step approach is proposed. The first step consists of evaluating the impact on traffic through micro-simulation, performed considering the variation of transport demand over time. This allows the evaluation of the level of service parameters, such as queue length and travel time delay due to traffic limitations and work zone presence.

In the second step, the results of pavement condition analysis are translated into degradation levels and the work zones to be planned are suggested.

In the third step, the work zone scheduling is defined through an optimisation model able to allocate work zones to time intervals and to define the best work zone configuration to mitigate the impact on highway traffic flow.

A solution algorithm is proposed to deal with the complexity of the planning model, solving big instances.

The approach is applied to a real case study within the Horizon 2020 European project OMICRON. The results show the effectiveness of the proposed approach in minimizing the effects of maintenance execution on traffic while guaranteeing high infrastructure reliability.

1. Introduction

Highways are perceived as vital arteries of economic activities through connecting regions and facilitating transportation. However, their far-reaching impact extends beyond economic significance. They enhance accessibility, improve overall connectivity, reduce congestion, and lead to lower fuel consumption [1]. The use of transport infrastructure brings about its deterioration. Consequently, adequate and sustainable maintenance planning is becoming fundamental. As highways consist of various components, their maintenance also includes numerous work activities to restore the highway to a condition close to its original state [2].

Appropriate and timely maintenance of highways is mandatory for the safety of road users. However, this task leads to impacts on traffic, productivity, environment, and requires technological developments. The decision-making process for highway maintenance planning has progressed over the years to improve the safety of highway users and to maintain an adequate level of service. This process involves various inputs to develop accurate and optimal plans for the restoration of highways including but not limited to resource availability, traffic demand, condition of the assets, etc. The result of such decisional processes is an optimal plan compliant with the economic, technical, and social requirements [3]. In the big data era, maintenance planning has also been revolutionized due to the vast amount of data being generated continuously on transport networks. Therefore, data analysis became a key step in the maintenance planning process for transport infrastructure. Some studies already applied optimisation techniques and data-driven approaches to assess how maintenance activities affect users

* Corresponding author.
E-mail address: alice.consilvio@unige.it (A. Consilvio).

https://doi.org/10.1016/j.treng.2025.100381
Received 30 December 2024; Received in revised form 30 May 2025; Accepted 31 July 2025
Available online 5 August 2025
2666-691X/© 2025 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

in railways and public transport [4,5], however, the application of these types of approaches to highway networks has not received the deserved attention yet.

Highway maintenance planning can be divided into three levels: operational planning, tactical planning, and strategic planning. The operational level regards short-term planning and involves factors such as weather conditions, available resources, and short-term operational limitations, dealing also with unexpected failures and the consequent corrective maintenance interventions. The critical aspect related to operational planning is dealing with deviations from the defined plan and defining recovery strategy such as the replanning of the available resources (Yu et al. [6]). Tactical planning, on the other hand, focuses on planning decisions on a mid-term time horizon such as the offline planning of preventive maintenance activities and the definition of the related work zones. Doing this assumes the availability of the needed resources (such as machinery and maintenance teams) and the availability of traffic and infrastructure condition data (Aad et al. [7]). At a strategic level, the needed maintenance investments on a long-term horizon are estimated and prioritise considering the budget resources and the transport demand evolution; the alignment with regional and local policies; external influencing factors, such as socio-economic factors; and future trends, such as climate change. The critical aspect is the comparison of long-term scenarios which require reliable prediction models of traffic demand and infrastructure degradation (de Medeiros Pereira et al. [8]).

This work focuses on the tactical level of maintenance planning, based on the assumption of a sufficient budget, previously allocated at a strategic level, and alignment with existing trends and policies analysed at the strategic level through a what-if scenario comparison. In addition, the availability of resources is assumed and only preventive maintenance activities are considered, since unexpected disruptions, such as unexpected failure and maintenance teams' unavailability will be addressed at the later operational stage, as well as the deviations from the defined plan. Therefore, both the detailed allocation of resources and maintenance teams and the identification of long-term trends are outside the scope of this paper.

This paper aims to optimising work zone planning to alleviate the traffic impacts of highway maintenance activities while keeping a high level of infrastructure quality and maintenance efficiency. To do this, a multi-objective decision-making approach is provided for work zone planning by considering traffic impacts and pavement condition analysis. The traffic impacts are analysed through microsimulation, while the pavement condition is estimated through a machine learning technique. The results of both the analysis are then used as inputs in the maintenance planning. An algorithm for the suggestion of work zone length and the assignment of work zones to the different months of the year is presented. To demonstrate the results, a real case study has been conducted showing the applicability of the proposed approach.

In more detail, the proposed framework is aimed at improving the maintenance of highway pavement moving towards user-oriented predictive maintenance strategies. Therefore, the goal is twofold. On one hand, it shows how the available data can be used to develop predictive approaches to estimate the status of highway pavements and how the results of condition analysis can be used in the planning; on the other hand, it shows how user-oriented objectives can be considered estimating the impacts on the final users.

Therefore, it supports the infrastructure manager in choosing the best maintenance policy in the definition of the yearly plan, comparing a maintenance policy based only on condition and a maintenance policy which consider also impacts the final users.

This paper is structured as follows: Section 2 presents a literature review on highway maintenance planning and maintenance work zone's decision-making. Section 3 outlines the proposed methodology. The solution algorithm is detailed in Section 4. Section 5 discusses the applicability of the proposed approach, Section 6 describes the case study, and the results are presented in Section 7. Finally, Section 8 concludes the paper by summarizing the main insights and providing suggestions for future research.

2. Literature review

2.1. Highway maintenance decision-making

Ensuring the maintenance and rehabilitation of highways is essential to maintain an adequate level of service for road users. Although asset management tools have already been applied to support decision-making, there is still a need to improve their effectiveness. Shah et al. [9] focused on the challenges and potential applications of using asset management principles (AMP) in a highway maintenance agency or department. It is noted that ineffective implementation of AMP in highway maintenance can lead to significant negative impacts. Additionally, the importance of improving asset management capabilities, considering the optimal use of resources and data about assets, is emphasized. Tee and Ekpiwhre [10] developed a strategic cost model to facilitate effective decision-making for highway asset maintenance by integrating asset condition levels and anticipated maintenance costs. The findings suggest the most effective maintenance plan for the upcoming years. These models provide valuable insights for strategic-level decision-making in highway maintenance, however, the usage of data about infrastructure conditions is missing as well as the estimation of traffic impacts.

In recent decades, the growing amount of available data has led researchers to focus on the development of predictive models for the estimation of pavement conditions. Li et al. [11] introduced a groundbreaking predictive maintenance approach that leverages a decade-long database and Deep Learning algorithms. This database incorporates diverse factors such as maintenance records, distress measurements at fixed intervals, traffic load data, and climatic history. Their study highlights the potential of hybrid neural networks (HNN) to accurately forecast highway distress, offering a pathway to optimise long-term maintenance strategies. Han et al. [12] addressed the issue of increasing the accuracy of predictive models by utilising an improved weight random forest algorithm (IWRF) combined with an analytic hierarchy process (AHP) to assess road pavement conditions. To enhance accuracy and efficiency as well as to provide a systematic mapping process for creating maintenance decision plans, Han et al. [13] proposed an intelligent decision-making model for pavement maintenance based on the reinforcement learning (RL) concept. Specifically, the model utilises the proximal policy optimisation algorithm. A method for constructing an RL environment is introduced based on a deep artificial neural network, and a reward function is designed for road maintenance decisions. Yet the studies lack the optimisation of maintenance planning according to multiple criteria.

Recent advancements in intelligent decision-making frameworks are transforming the process of highway maintenance planning, including several aspects. Pourgholamali et al. [14] conducted an exhaustive review of multi-objective optimisation problems in highway pavement rehabilitation and maintenance, shedding light on current solution techniques and laying the foundation for a structured taxonomy of maintenance planning at different planning levels. Considering long-term planning, sustainability aspects, such as socioeconomic and demographic factors and externalities, have been introduced and addressed by some studies. Cao et al. [15] introduced a novel bi-level optimisation model, in response to the complexities of managing extensive road networks. This model segments road networks into subnetworks based on highway class, traffic volume, and natural zoning criteria. Using iterative calculations and a genetic algorithm, the model effectively addresses maintenance challenges in large-scale road systems, offering strategies that promote the sustainable development of road infrastructure.

The importance of traffic aspects within the sustainability goals of road maintenance is mentioned by Naseri et al. [16] who combined ensemble learning techniques with a multi-objective metaheuristic optimisation algorithm for Pavement Maintenance and Rehabilitation (M&R) planning, considering externalities. To account for traffic impact, minimizing road closure is considered alongside minimizing greenhouse gas emissions, minimizing M&R cost, and minimizing the International Roughness Index (IRI). The findings indicate that the developed hybrid method can provide optimal M&R plans for large-scale networks.

Borghetti et al. [17] and de Medeiros Pereira et al. [8] introduced operative methodologies to prioritise programmed maintenance interventions including the traffic volume as one of the prioritisation criteria. The approach proposed by Borghetti et al. [17] incorporates road characteristics, the purpose of interventions, and specific maintenance needs, including information about the asset location, such as the average daily traffic, the accidentality, and the related social cost. This methodology, validated on the Italian road network, demonstrates the utility of (Geographic Information System) GIS tools in creating thematic maps that reduce human subjectivity and enhance maintenance planning.

The prioritisation framework provided by de Medeiros Pereira et al. [8] represents a geospatial-based systematic process for prioritising highway segments for maintenance and rehabilitation. By ranking highway segments based on geographic context and operational characteristics, the method incorporates socioeconomic and demographic factors alongside traditional engineering considerations such as transport infrastructure, traffic volume, highway capacity, pavement condition, surface drainage, and weather-related data. A macroscopic traffic simulation tool is applied for the static adjustment of the Origin-Destination (OD) matrix. The proposed GIS-oriented Delphi framework ensures efficient allocation of funds across Brazilian highways.

However, these strategic approaches focus on the long-term and do not consider the impacts of maintenance work zones on traffic and their specific configuration.

A first step toward the consideration of user costs and work zone configurations in mid-term planning is provided by Donev and Hoffmann [18] and Aad et al. [7].

Donev and Hoffmann [18] dealt with pavement data of short survey sections, estimating travel delay costs for each road section, the direction of travel, and work-zone layout using a macroscopic demand-capacity model.

Aad et al. [7] developed a systematic and comprehensive methodology to optimise the allocation of networkwide pavement treatment work zones over space and time. However, they considered work zones of complete road section closure and applied large-scale hybrid macro/*meso* traffic simulative approaches to identify the best traffic control and management strategy.

An appropriate evaluation of maintenance work zones' impacts on traffic is addressed at the short-term level by Yu et al. [6] who proposed a mixed multi-object nonlinear program (MNLP) model for short-term activity assignments to maintenance teams and time windows in urban work zones. They model scenarios of different speed limit control strategies and different work zone configurations. However, the application is limited to a small case study of 6 work zones and three maintenance teams. In addition, the travel time delay is evaluated according to an All-or-nothing traffic assignment.

Together, these advancements illustrate a paradigm shift in highway maintenance decision-making. From predictive analytics and intelligent algorithms to geospatial prioritisation and multi-objective optimisation, these innovations address the multifaceted challenges of modern road infrastructure management. Notwithstanding, an integration of pavement condition analysis and traffic flow impacts simulations in the decision-making process of maintenance planning is identified as a gap to be covered by the current study. In particular, since traffic delays can result in significant social costs borne by users, studying how and to what extent traffic delays affect optimal decision-making is critical for infrastructure management policy (Sasai et al. [19]).

Therefore, the present paper focuses on the comparison of different optimal policy schemes (i.e., minimizing only costs to the infrastructure managers related to the maintenance activity execution and the infrastructure reliability vs. minimizing the sum of user and infrastructure managers' costs).

In addition, the present paper significantly extends the work by Abbasi et al. [20] which integrates traffic simulation and optimal planning of work zones considering a small case study of 15 work zones. In particular, the present paper introduces the estimation of pavement condition and develops ad-hoc algorithms to suggest the work zone length and to solve big instances of the problem, covering a yearly time horizon.

A comparative analysis of the mentioned existing works about road maintenance planning is provided in Table 1.

2.2. *Maintenance work zone impact on traffic*

The flow of traffic on highways mimics the flow of fluids in any pipeline. It remains streamlined as long as there is no disruption. However, the maintenance work zones create hindrances in the smooth traffic flow by reducing the carriageway capacity. This reduction generates a negative impact on service level characteristics of traffic flow resulting in congestion.

The assessment of construction work zones' impacts on traffic, based on simulation, has traditionally addressed specific scopes such as the understanding of driver behaviour or the evaluation of safety aspects. Research concerning driver behaviour is provided by Hang et al. [21] who conducted a simulation-based study to understand lane-changing behaviour in work zones. Their conceptual model divides the process into perception, preparation, and action stages, identifying key factors such as lane-end sign distance and traffic volume. Notably, the location of the lane-end sign significantly influences driver perception and behaviour, providing valuable insights for designing traffic control measures in construction zones. Raju et al. [22] analysed lateral driving patterns in construction work zones under heterogeneous traffic conditions. Their video-based surveys revealed reduced lane efficiency due to lower stream speeds, highlighting the critical nature of work zones.

Regarding the safety aspects, Saha and Sisiopiku [23] worked on the operational and safety impacts of different temporary traffic control (TTC) approaches in work zones featuring a three-to-one lane drop configuration using VISSIM simulation modelling. Static late merge and early merge, as two TTC strategies, were concentrated on long-term and short-term lane closure configurations. The outcomes provided valuable insights into how various traffic control strategies affect important factors like traffic density, speed, and travel time. Ge et al. (2020) studied the optimal length of warning zones in freeway work zones and the relationship between warning zone length and safety evaluation index through microsimulation techniques and a surrogate safety assessment model. The results show that under different traffic conditions, travel time and delay increase slowly with the increase of warning zone length; traffic conflicts decrease with the increase of warning zone length.

However, only a few studies addressed this problem to provide inputs to decision-makers for improving maintenance planning.

Among them, one distinction is related to the time horizon of the traffic prediction.

Considering a long-term analysis, Bae et al. [24] introduced a multi-contextual quantitative method utilising big data for urban highway construction zones. Their analytical model evaluates the effects of different lane closure scenarios and predicts traffic pattern responses, validated across three downtown locations. This approach provides a robust framework for assessing construction impacts, emphasizing the need for comprehensive and adaptable methodologies.

Regarding a short-term horizon, Mekker et al. [25] explored the integration of connected vehicle traffic data and LiDAR-generated geometric data to evaluate how work zone geometry affects traffic operations. This approach allowed for precise identification of congestion

Table 1
Overview of existing studies on road maintenance planning.

Reference	Work zone prioritising/ planning	Planning horizon	Objective function	Constraints	Traffic analysis	Road condition analysis	Instance size
Tee and Ekpiwhre [10]	✓	Long- term	Minimize treatment cost	Available budget	–	✓	Big
Li et al. [11]	–	–	–	–	–	P	Big
Han et al. (2022)	–	–	–	–	–	✓	Big
Han et al. [13]	✓	Long- term	Pavement condition and maintenance cost	Thresholds of pavement condition parameters	–	✓	Big
Cao et al. [15]	✓	Long-term	Equivalent mileage, vehicle axle load action, Pavement performance	Budget constraints and performance thresholds	–	✓	Big
Naseri et al. [16]	✓	Long-term	Greenhouse gas emission, M&R cost, pavement condition, road closure duration	Thresholds of pavement condition, budget	–	✓	Big
Borghetti et al. [17]	✓	Long-term	Intervention Category; Asset location; Asset Typology	–	–	–	Big
de Medeiros Pereira et al. [8]	✓	Long-term	socio-economic and demographic perspectives, engineering characteristics	–	Macroscopic traffic simulation for "Static OD Adjustment"	–	Big
Donev and Hoffmann [18]	✓	Long- term	Minimisation of agency, road user, and environmental costs	Annual budget, available capacity, work zone layout, and traffic control	Macroscopic demand-capacity analytic model	✓	Big
Aad et al. [7]	✓	Mid-term	Maximize pavement performance and minimize travel time	Deterioration threshold and deadlines	Macro/*meso* traffic simulations	–	Small
Yu et al. [6]	✓	Short-term	Traffic safety maintenance efficiency, travel delay	Time window, Traffic safety, Workload	And All-or-nothing traffic assignment	–	Small
Abbasi et al. [20]	✓	Mid-term	Maintenance efficiency and traffic impact terms	Number of active work zones, execution deadlines	Traffic microsimulation	–	Small
Current work	✓	Mid-term	Condition-based terms and traffic impact terms	Number of active work zones, execution deadlines, work zone configurations	Traffic microsimulation	✓	Big

points, offering actionable insights to improve traffic flow.

Another important distinction is related to the applied approach. Existing studies exploit macroscopic, mesoscopic, and microscopic traffic models and simulations.

Concerning the macroscopic models, Bharadwaj et al. [26] examined the relationship between work activities and traffic conditions. They developed a methodology using speed–flow curves and adjustment factors to quantify the impact of bridge and pavement-related activities. Their findings demonstrated the effectiveness of the Van Aerde model [27] in analysing traffic flow characteristics and highlighted the advantages of using LiDAR technology to minimize risks for inspectors in active work zones. Silvestri et al. (2025) [28] applied mesoscopic traffic simulation models to assess different maintenance scenarios under varying demand levels (i.e., during the rush hour and off-peak hours, weekdays and weekends, summer and winter months) and vehicular compositions (i.e., percentage of heavy vehicles), to identify the scenario that minimizes the impacts on users. However, they did not test different work zone configurations and did not use the results within a planning framework.

Lastly, Chy and Sisiopiku [29] explored freeway performance under varying lane closure setups using a microsimulation model of a 10-mile segment. Their study revealed that while the length of the work zone had minimal impact on the travel time index, an increase in truck traffic beyond 15 % significantly exacerbated freeway congestion.

As mentioned, our previous study (Abbasi et al. [20]) integrated traffic microsimulation and optimal planning of work zones by simulating the impact of different work zone configurations. However, the evaluation of infrastructure conditions is not addressed.

Therefore, despite significant advancements in understanding traffic flow impacts and driver behaviour in construction work zones, a critical gap persists in integrating traffic impact analysis with pavement condition assessments. The absence of a unified methodology that simultaneously addresses traffic disruptions and pavement maintenance planning hinders the development of comprehensive strategies for optimising highway maintenance activities. The unified methodology proposed in the current work fills the gaps revealed in the present state-of-the-art.

In more detail, compared to the reference literature, the contributions of this paper consist of:

- planning maintenance by taking into account the impact on users, in terms of travel time and delays. In particular, compared to existing studies, such as Tee and Ekpiwhre [10] and Han el [13], the proposed model includes in the objective function traffic-related terms, integrating traffic simulation and maintenance planning;
- computing the impact on traffic of specific work zone configurations, in particular, comparing the effects of a one-lane closure configuration and a traffic deviation to the opposite carriageway;
- addressing the issue of highway reliability and improving pavement condition, through the data-driven estimation of the status of each highway segment. Compared to existing works, such as Borghetti et al. [17] and de Medeiros Pereira et al. [8], this study includes the results of pavement conditions analysis within the optimisation model;
- supporting infrastructure manager in the definition of the work zone length according to the homogeneous conditions of road segments, and their position with respect to the toll gates, through a dedicated merging algorithm;
- supporting infrastructure manager in evaluating the impact of their yearly maintenance plan computing some indicators of performance which include traffic-based and condition-based factors;
- testing a user-oriented predictive maintenance approach, comparing the results of different maintenance policies (i.e., minimizing only costs for the infrastructure managers related to the infrastructure

condition vs. minimizing the sum of user and infrastructure managers' costs).

It is worth emphasizing that the approach considers tactical planning of highway maintenance, aimed at prioritising the highway sections to be maintained and allocating them to the best time window within a yearly time horizon. Therefore, the proposed approach does not consider operational aspects such as the allocation to maintenance teams and the availability of equipment which are addressed at a later stage within the short-term maintenance planning.

In addition, it is an offline planning which neglects unexpected events, such as corrective maintenance activities and bad weather conditions which may imply deviation from the defined tactical maintenance plan, since these events are addressed in the context of the real-time/dynamic planning. Therefore, these aspects are outside the scope of this study. In addition, regarding the estimation of the traffic demand, it does not consider the effects of macro trends on the demand variation, but only fluctuations among peak days and off-peak days, week and weekend days, and fluctuations due to seasonality (holidays, school periods, etc.). Table 2 provides a comparison of the discussed works related to road maintenance traffic impacts.

3. The proposed methodology

Fig. 1 provides an outline of the proposed methodology. A three-step approach is applied to derive highway maintenance planning by considering different work zone configurations:

- Step 1: Traffic simulation is applied to analyse work zones' impacts on traffic flow by using microsimulation software. Real traffic data are used as simulation input values. Then, the outputs of the simulation (queue length and delay time) are used as part of the inputs for mathematical modelling.
- Step 2: Infrastructure condition results are translated into degradation levels to integrate them into the planning model. To this aim, the merging algorithm, described in Section 4, is developed to deal with the different granularity between pavement analysis and operational work zones. The merging algorithm suggests the work zone length (best segments to be merged) according to homogeneous degradation level and close position. The output consists of the definition of work zones' initial and final kilometric points, given the maximum and minimum realistic length values according to the infrastructure manager's operational constraints.
- Step 3: The Mixed-Integer Linear Programming (MILP) model is defined, and the solution algorithm is applied to solve it to obtain the yearly maintenance plan.

3.1. Pavement condition analysis

In this paper, as part of the maintenance planning framework, historical data relative to pavement status is analysed and used through machine learning techniques to make predictions on the pavement status which supports the maintenance planning.

The considered data include different road condition parameters: Side Force Coefficient (SFC), IRI, and Texture (TEX) over 9 years. Three supervised learning regression methodologies were applied and compared:

- *Linear Regression model*. The target value is expected to be a linear combination of the features following Eq. (1):

Table 2
Overview of existing studies on maintenance impacts on traffic.

Reference	Scope	Methodology	Maintenance planning	Time horizon	Data	Performance indicators
Hang et al. [21]	Model lane-changing driving behaviour	Driving simulator	–	Short-term	Forty-two participants in the simulation driving	Duration of perception, preparation, and action stages
Raju et al. [22]	Lateral driving behaviour under the influence of the work zone	Microscopic & Macroscopic Simulation	–	Short-term analysis	Trajectory data	Relative speed and distance
Saha and Sisiopiku [23]	Assessing traffic control options and safety aspects	Microscopic simulation	–	Short-term analysis of peak and off-peak data	Hour-by-hour traffic data on a typical weekday	Traffic density, speed, travel time, and flow
Ge et al. [30]	To determine the length of warning zone of freeway work zones	Micro Simulation model and surrogate safety assessment model	–	Short-term	Expected speed and traffic volumes	Travel time, delay, traffic conflict, safety evaluation index
Bae et al. [24]	Long-term assessment of construction impacts	Multicontextual Machine-Learning Approach	–	Long-term	traffic sensors, weather, and sociodemographic data	Travel time delays
Mekker et al. [25]	Non-conforming geometric conditions in work zones	Data-driven approach	–	Short-term	LiDAR geometric data; connected vehicle speed data	Speed performance
Bharadwaj et al. [26]	Impact on traffic flow according to work zone type	Macroscopic stream modelling	–	Short-term	Traffic flow by sensors and probe data	Capacity reduction factor and speed reduction factors for work zones
Silvestri et al. (2025) [28]	Impact of varying demand levels and vehicular compositions	mesoscopic simulation model and dynamic traffic assignment	–	Mid-term	Hourly origin-destination matrices	Monetized impacts of traffic congestion
Chy and Sisiopiku [29]	Impacts of different combinations of lane closures, TTC strategies, and work zone lengths	Micro simulation	–	Short-term	Hour-by-hour traffic data on a typical weekday, heavy vehicle percentage	Travel Time Index
Abbasi et al. [20]	Investigate traffic impacts of different work zone configurations	Traffic microsimulation	P	Mid-term	Traffic flow data	Average queue length and travel time delay
Current work	To optimise and prioritise highway maintenance by considering both condition-based and traffic-based factors	Traffic microsimulation & Mixed Integer Linear Programming	P	Mid-term	Maintenance, pavement condition, and traffic flow data	Average queue length and travel time delay

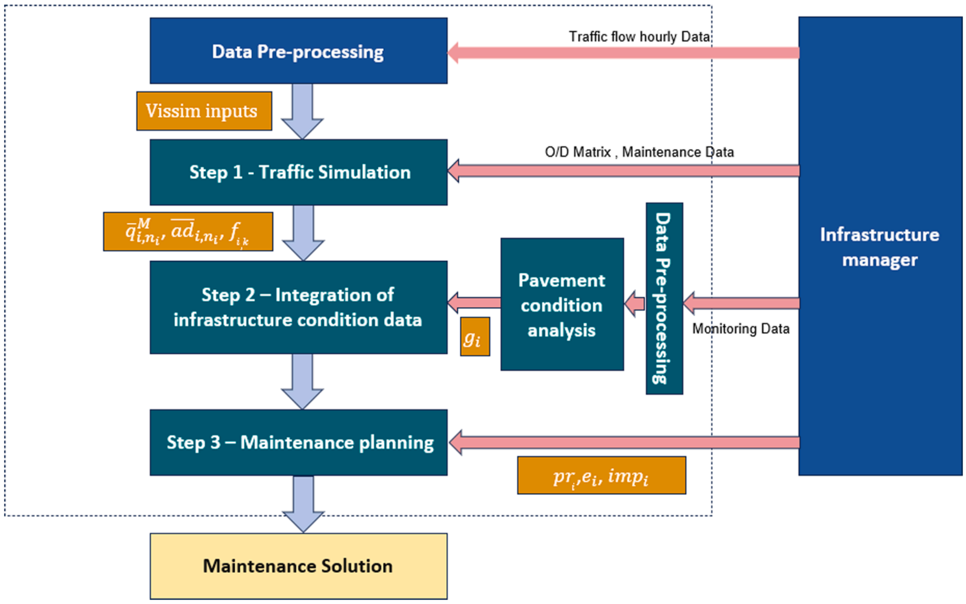

Fig. 1. The maintenance planning framework (notation provided in Table 3).

$$y(w,x) = w_0 + w_1x_1 + \ldots + w_px_p \quad (1)$$

Where y is the predicted value, x the data available, $w = (w1, \ldots, wp)$ the weights and w_0 the intercept.

- *Decision Tree.* It recursively partitions the data into subsets based on feature values, aiming to create a tree-like model of decisions. Each internal node represents a decision based on a feature, leading to branches representing possible outcomes, and leaf nodes denote the final predictions or decisions.
- *Random Forest.* It is an ensemble learning method that constructs multiple decision trees during training. Each tree is trained on a random subset of the data and a random subset of features, and predictions are made by aggregating the predictions of individual trees. This approach improves predictive accuracy, reduces overfitting, and enhances robustness compared to single decision trees.

Besides these models, a baseline (or trivial result) is applied to mark a limit on what the model should improve, in which the prediction is the mean value of all the previously measured values.

To apply the different methodologies, the workflow defined in Fig. 2 is followed.

The first step, called the Data Process, includes all the tasks related to preparing the dataset for analysis. Once the dataset is ready, it is split, within step 2, into a training dataset and a test dataset. The purpose of this split is to fit the model with the training dataset in step 3 "Model fitting", so in step 5, the prediction can be performed on data that has not been used for training, ensuring an unbiased evaluation. Step 5 produces the pavement predictions, which are evaluated in step 6. Step 4 is necessary to tune the model's hyperparameters.

Data process steps are applied to different approaches to find the most suitable option. The objective is to maintain a high data volume suitable for machine learning while dealing with the overlap of the different datasets and the lack of maintenance data that corresponds with the improvement of the pavement over the years:

- *Use of all data*. This is the most direct approach to see which results can be obtained from the selected models if all the provided data are used independently from the maintenance step. Two options are tested:
  - *Use of all data with data from the same year*. This implies that to predict the values of a parameter for a specific year, also data from that same year for the rest of the parameters are used.
  - *Use of all data without data from the same year*. This implies that to predict the values of a parameter for a specific year, only data from previous years are provided.
- *Use of only degradation data.* In this case, it is assumed that, if there is a worsening of the pavement parameters from one year to the following one, no maintenance was executed in those locations, and therefore only those degradation data are selected to perform the analysis. Only degradation data are used to predict degradation trends. Three cases are considered:
  - *Use of only degradation data without time dimension.* The parameters are predicted only based on the previous values of pavement parameters and the related lane direction.

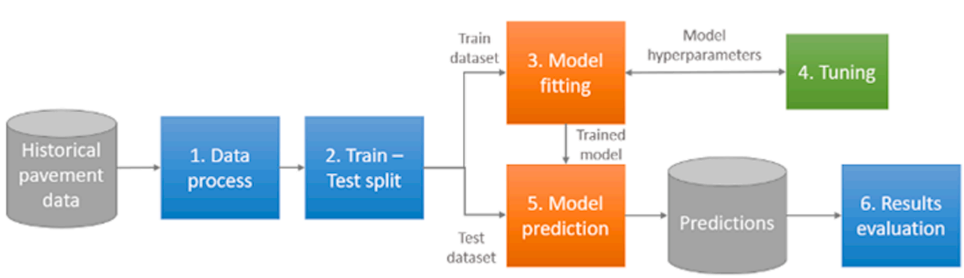

Fig. 2. Pavement prediction workflow.

- *Use of only degradation data with time dimension.* In this model also the initial time and the number of years passed between the initial and the predicted time are added as input variables.
- *Use of all data adding maintenance parameters.* This model uses all the data, but a "maintenance parameter" is added to indicate whether maintenance has been performed or not.

For each of the presented approaches, the three considered models (Linear Regression model, Decision Tree, and Random Forest) are trained using a training dataset obtained from a random split of proportion 80–20 %. In each case, the model hyperparameters are tuned by selecting the hyperparameters to tune and their possible values using GridSearchCV [31] a Python Scikit-learn function that performs an optimised cross-validated grid-search on the values. The mean squared error, mean absolute percentage error, median absolute error, and max error are chosen as indicators to evaluate the prediction performance.

Once the three considered parameters SFC, IRI, and TEX are predicted, the state of the pavement is evaluated based on the methodology proposed by the COST Action 354 "Performance Indicators for Road Pavements" [32]

This methodology takes the values of pavement parameters to calculate performance indicators (PIs) that assess conditions relative to friction, texture, and evenness. These are combined into combined performance indicators which assess qualities such as comfort and safety and finally, these are englobed inside a global performance indicator (GPI). These indexes are provided by equations from (2) to (7).

Performance Indicators (PI)

$$\textbf{Friction}:\ \mathrm{PI_F} = \mathrm{Max}(0; \mathrm{Min}(5; (-17.600\ \mathrm{SFC} + 11.205))) \tag{2}$$

$$\textbf{Macro} - \textbf{texture}:\ \mathrm{PI_T} = \mathrm{Max}(0; \mathrm{Min}(5; (7 - 6.9\ \mathrm{TEX})) \tag{3}$$

$$\textbf{Evenness}:\ \mathrm{PI_E} = \mathrm{Max}\left(0; \mathrm{Min}\left(5; \left(0.1733\ \mathrm{IRI}^2 + 0.7142\ \mathrm{IRI} - 0.0316\right)\right)\right) \tag{4}$$

Combined performance indicators (CPI)

$$\textbf{Comfort}:\ \mathrm{CPI_C} = \mathrm{Min}(5; \mathrm{I_1} + \frac{p}{100}\overline{\mathrm{I_2} + \mathrm{I_3} + \ldots} = \mathrm{Min}\left(5; \mathrm{W_E PI_E} + \frac{p}{100}\mathrm{W_T PI_T}\right) \tag{5}$$

$$\textbf{Safety}:\ \mathrm{CPI_S} = \mathrm{Min}(5; \mathrm{I_1} + \frac{p}{100}\overline{\mathrm{I_2} + \mathrm{I_3} + \ldots} = \mathrm{Min}\left(5; \mathrm{W_F PI_F} + \frac{p}{100}\mathrm{W_T PI_T}\right) \tag{6}$$

General Global Indicators (GPI)

$$\textbf{GPI}\ \mathrm{GPI} = \mathrm{Min}\left(5; \mathrm{I_1} + \frac{p}{100}\overline{\mathrm{I_2} + \mathrm{I_3} + \ldots} = \mathrm{Min}\left(5; \mathrm{W_C CPI_C} + \frac{p}{100}\mathrm{W_S CPI_S}\right) \tag{7}$$

According to the GPI values, four different degradation levels (excellent, good, poor, and critical conditions) are defined for each highway segment of 0.25 km and each direction.

The defined degradation level for each segment is then used by the merging algorithm, described in Section 4, to suggest the work zone length, and by the planning model described in Section 3.3 to define the maintenance plan.

3.2. Traffic simulation

In this paper, traffic simulation is used to analyse different work zone configurations and their impacts on traffic flow. A microscopic simulative approach is applied by using the software PTV VISSIM®.

Car-following models are a fundamental component of traffic simulations. They dictate how vehicles behave in response to the movements of the vehicles ahead of them. Customizing these models becomes increasingly important when simulating scenarios like maintenance work zones, where driving behaviours are often disrupted by changes in the road environment, such as lane narrowing or reduced speed limits. The changes in these contexts ensure that the simulation more accurately reflects the conditions drivers face.

By customizing car-following rules, the simulation can more accurately predict the overall impact of different work zone configurations, particularly the queue length and delay time, on traffic flow. The customization is achieved by setting parameters for the standstill distance, headway time, desired speed, acceleration, deceleration, and following vehicle behaviour. In particular, to reflect the cautious behaviour of drivers in the presence of a work zone with lane reduction, the car-following model is adjusted to increase the following distance and decrease the maximum acceleration rate, reduce aggressiveness, and increase courtesy by using the factors provided by Chy and Sisiopiku [29] and Saha and Sisiopiku [23].

Real traffic data and road geometry data are used as simulation inputs. These input data consist of traffic volumes, speed variations in different road sections, traffic composition, and work zone configuration. Fig. 3 provides detailed illustrations of two different work zone configurations: lane closure configuration and traffic deviation in a two-lane per-direction highway section. The main outputs of the simulation model to assess the performance of the traffic network under different conditions are as follows:

- the average maximum queue length $\overline{q}^M_{i,n_i}$ caused by the work zone in the road section i with configuration $n_i \in N$
- the average delay time $\overline{ad}_{i,n_i}$ caused by the work zone in the road section i with configuration $n_i \in N$.

These simulation outputs are exploited as part of the inputs for the mathematical planning model described in the next section.

3.3. Mathematical formulation

In this Section, the mathematical formulation of the proposed model is presented. Specifically, the model is composed of a Mixed-Integer Linear Programming (MILP) problem aimed at allocating maintenance interventions to specific time intervals in the considered time horizon and at defining the best configuration strategy.

The road is divided into $|\mathrm{R}|$ sections according to homogeneous conditions (degradation level) and length compatible with work zones' operational requirements. This ensures that each section is homogeneous in terms of maintenance needs and suitable for the practical implementation of work zones. Then, a set $\mathscr{A} \subseteq \mathrm{R}$ is defined as the set of road sections needing maintenance according to their degradation level.

The model deals with the optimal allocation of maintenance activities to time intervals at the tactical level by taking into account the transport demand and the operational constraints related to traffic management rules. The assumptions of the model are:

- N is the set of all possible configurations for each work zone i, where each possible configuration is defined by regulation and by the operational constraints of each case study. The configuration consists of the closure of one or more lanes and/or the deviation of the traffic flow in the opposite carriageway.
- each work zone remains in place until the end of the maintenance intervention;
- time horizon is given by a set K of time intervals, and it guarantees the accommodation of all the maintenance interventions;
- following a realistic scenario, the duration for each maintenance intervention p_{i,n_i} is fixed and known in advance and depends on the work zone configuration n_i ;

(a)

(b)

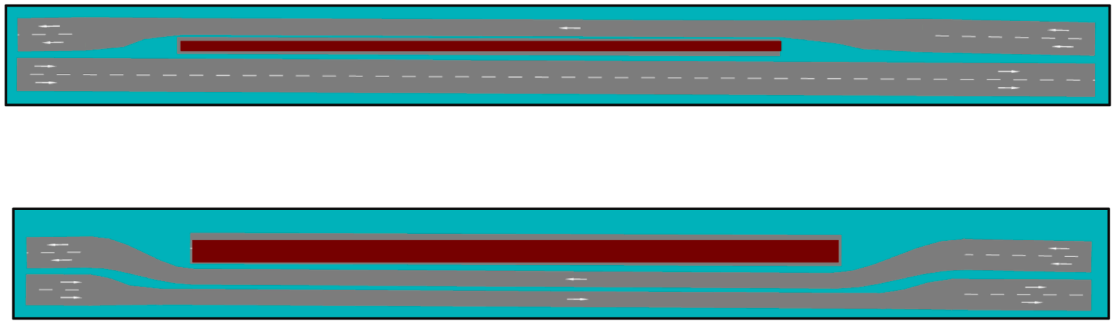

Fig. 3. (a) One lane closure configuration scheme, (b) Traffic deviation configuration scheme (from PTV Vissim).

- maximum S road sections can be maintained at the same time;
- the setup time required to move the work zone is considered negligible concerning the duration of the maintenance activities;
- the traffic flow fluctuations are considered known during the considered time horizon and not affected by new transport policies or socio-economic macrotrends;
- the needed resources (e.g. maintenance teams) are considered available at a tactical level. However, a maximum number S of sections that can be maintained at the same time is considered to keep into account the resource limitation.
- only preventive maintenance activities are considered (no unexpected failures or corrective interventions) since it is offline planning at the tactical level;
- unexpected external events, such as adverse weather conditions, are neglected in the offline planning.

Each road section needing maintenance $i \in \mathscr{A}$ is characterized by a priority

pr_i of maintenance execution, a degradation level g_i, a maintenance deadline e_i, a total duration p_{i,n_i} of the intervention according to the work zone configuration n_i , the importance imp_i of that section of the highway and the traffic volume $f_{i,k}$ in road section i during time interval k.

The decision to be made consists of the definition of:

- the optimal allocation of work zones to time intervals;
- the order in which the road sections need to be maintained;
- the suggested configuration of the scheduled work zones according to its impact on traffic, chosen among the possible admissible options.

The objective function's goal is to minimize the combined impact of maintenance needs and traffic disruptions. From the maintenance needs point of view, it accounts for the time needed to complete repairs in each road section i.e. $in_i + p_i$, the priority of those repairs pr_i, and how badly the infrastructure has deteriorated g_i. From the traffic point of view, it considers factors like the maximum queue length $\overline{q}^M_{i,n_i}$, average travel delays $\overline{ad}_{i,n_i}$, traffic volume i.e. $f_{i,k}$ in each section on a given time interval, and how important that section is to the overall road network imp_i. To ensure smooth operations, the constraints require that all necessary maintenance be finished before the deadlines and within the available schedule to keep the road in good condition. They also ensure that too many work zones do not overlap; S is the maximum number of sections that can be maintained at the same time, avoiding major traffic disruptions.S

The mathematical details of the problem are outlined using the notation in Table 3.

Table 3
Notation of the problem.

	Processing time of maintenance intervention in road section i, expressed in several time intervals, with work zone configuration $n_i \in$ N
e_i	Deadline for the maintenance intervention in road section i
S	Maximum number of sections to be maintained at the same time
pr_i	Priority of maintenance intervention in road section i
$f_{i,k}$	Average traffic volume in road section i at time interval k
imp_i	Index of road section importance in terms of volume of traffic
g_i	Degradation of road section i
w_j	Coefficients calibrated to make the objective function j-th term comparable.
μ	Weight of the objective function term chosen according to infrastructure manager intentions ranging from 0 to 1.
$\overline{q}^M_{i,n_i}$	Average maximum queue length caused by the work zone in road section $i \in \mathscr{A}$ with configuration $n_i \in$ N
$\overline{ad}_{i,n_i}$	An average delay caused by the work zone in the road section $i \in \mathscr{A}$ with configuration $n_i \in$ N
Variables	
in_i	Starting time of maintenance intervention i
x^k_i	The binary variable is equal to 1 if the work zone in road section $i\in \mathscr{A}$ is active in the time interval k and 0 otherwise.
y^k_{i,n_i}	Binary assignment variable equal to 1 if the time interval k is the first for the intervention in road section $i\in \mathscr{A}$ with configuration $n_i \in$ N and 0 otherwise

$$\min \mu \left(w_1 \sum_{k\in H}\sum_{i\in \mathscr{A}}\sum_{n_i\in N} p_{i,n_i}\overline{q}^M_{i,n_i} y^k_{i,n_i} + w_2 \sum_{k\in H}\sum_{i\in \mathscr{A}}\sum_{n_i\in N} p_{i,n_i}\ \overline{ad}_{i,n_i} y^k_{i,n_i} + w_3 \sum_{k\in H}\sum_{i\in \mathscr{A}} f_{i,k}\ imp_i\ x^k_i \right) + (1-\mu)\left(w_4 \sum_{i\in \mathscr{A}} pr_i t_i + w_5 \sum_{i\in \mathscr{A}} g_i t_i \right) \tag{8}$$

subject to:

$$in_i = \sum_{k\in H}\sum_{n_i\in \mathrm{N}} k y^k_{i,n_i}\ \forall i \in \mathscr{A} \tag{9}$$

$$t_i = in_i + \sum_{k\in H}\sum_{n_i\in \mathrm{N}} p_{i,n_i}\ y^k_{i,n_i}\ \forall i \in \mathscr{A} \tag{10}$$

$$t_i \leq |H|\ \forall i \in \mathscr{A} \tag{11}$$

$$\sum_{k=e_i+1} x^k_{i,n_i} = 0\ \forall i \in \mathscr{A} \tag{12}$$

$$\sum_{i\in \mathscr{A}} x^k_{i,n_i} \leq S\ \forall k \in H \tag{13}$$

$$\sum_{n_i\in \mathrm{N}} y^k_{i,n_i} \leq 1\ \forall k \in H,\ \forall i \in \mathscr{A} \tag{14}$$

$$x^{imp}_{i,n_i} \leq 1 - \sum_{\forall n_i\in \mathrm{N}} y^k_{i,n_i}\ \forall i \in \mathscr{A},\ imp, k \in H : imp \leq\ k-1, k \in H,\ \forall n_i \in \mathrm{N} \tag{15}$$

$$x_{i,n_i}^{imp} \leq 1 - \sum_{n_i \in N} y_{i,n_i}^{k} \ \forall i \in \mathscr{A}, \ imp, k \in H: \ imp \geq \ k + p_{i,n_i} \ \ , imp \leq |H|, \ \forall n_i \in N \tag{16}$$

$$x_{i,n_i}^{imp} \ \geq y_{i,n_i}^{k} \ \forall imp, k \in H: \ k - 1 < imp < \ k + p_{i,n_i} \ \ , \ \forall n_i \ \in N \tag{17}$$

$$\sum_{k \in H} \sum_{n_i \in N} y_{i,n_i}^{k} = 1 \ \forall i \in \mathscr{A} \tag{18}$$

The objective function in Eq. (8) formalizes the goals outlined earlier, aiming at optimising the scheduling and completion of maintenance interventions. The constraints in Eq. (9) define the starting time of each maintenance intervention while Eq. (10) establishes the completion time for each intervention.

The constraints in Eq. (11) ensure that all maintenance interventions are completed within the overall time horizon, preventing any tasks from extending beyond the available period. Additionally, Eq. (12) guarantees that each intervention is completed before its respective deadline, ensuring the timely execution of each task.

In Eq. (13), the constraints define the maximum number of work zones that can be activated in any given time interval k. Eq. (14) further restricts the scheduling by ensuring that only one configuration can be assigned to each work zone, preventing conflicting assignments. Eqs. (15), (16), and (17) impose further rules regarding the continuity of maintenance interventions, ensuring that no task is split across non-consecutive time intervals (i.e., preemption is not allowed). Finally, Eq. (18) requires that each maintenance intervention has exactly one starting time interval within the considered time horizon, ensuring that all tasks are executed within the specified period without any overlaps.

It is worth noting that the coefficients. w_j in the objective function are calibrated to make the magnitude of the objective function terms comparable. They are technical coefficients of the models to be calibrated according to the considered case study.

Instead, the weight μ is set to model the importance of the condition-based and traffic-based objective function terms for the infrastructure manager and can vary in the range $[0, 1]$. The variation of this weight allows for the simulation of different maintenance policies. In detail, if μ is set equal to 0, only the costs for the infrastructure managers related to the infrastructure condition are minimised; if μ is set equal to 1, only the user costs are minimised.

Finally, concerning the road section definition, additional details about the subdivision of the road into sections, according to their condition and the work zone lengths, are provided in Section 4 with the description of the merging algorithm.

Regarding the problem complexity, as the planning horizon and the number of interventions increase, the computational time required to solve the problem, by using a commercial solver for the optimisation model, rises sharply. As shown in Fig. 4, for the 365-day planning horizon, increasing the number of interventions up to 25 does not significantly impact the computational time. However, when the number of interventions increases to 55, the computational time increases significantly. Furthermore, with 60 interventions, the solver is unable to process the problem. Since real-world applications often require planning over broad time horizons and handling a large number of maintenance activities, the need to overcome this computational issue has been recognised. To this aim, an ad-hoc solution algorithm able to efficiently deal with larger instances of the problem is developed and described in the following Section.

4. Solution algorithm

To improve the usability and scalability of this methodology, a solution approach that overcomes the mentioned computational limitation is developed. In this Section, the proposed solution approach, able to enhance computational efficiency while maintaining the quality of the maintenance scheduling solutions, is presented.

The solution approach is described in Fig. 5 and consists of two main algorithms:

- The merging algorithm, which suggests the work zones to be considered and their related starting and ending kilometric points, according to the degradation level of the highway segments provided by the condition analysis described in Section 3.1.
- The planning algorithm defines the assignment of the work zones to different aggregated time intervals (i.e. months) and their detailed planning with the allocation to each time interval (i.e. day).

The merging algorithm not only reduces the complexity of the problem by merging pavement segments into work zones but also enables the integration of infrastructure condition data. In particular, it allows for addressing the different levels of granularity between pavement analysis and operational work zones. Pavement analysis data is divided into 0.25 km segments, while the maintenance data provided by the infrastructure manager typically covers work zones longer than 0.5 km. The merging algorithm suggests the work zone length and starting

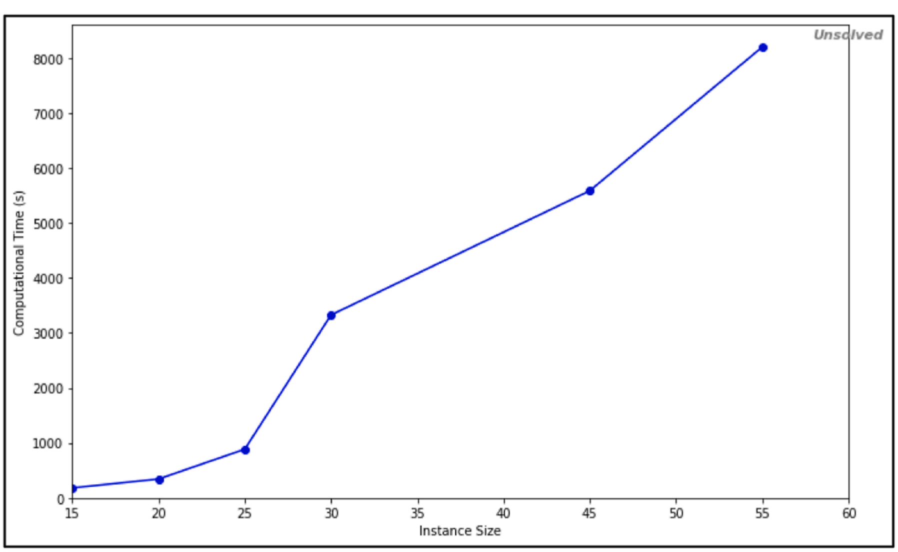

Fig. 4. Computational time for solving the problem with a 365-day planning horizon by using a commercial solver.

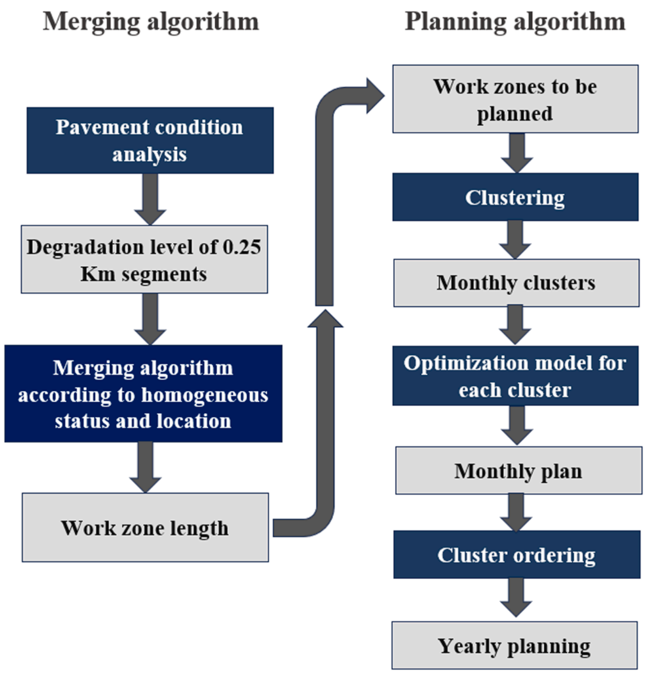

Fig. 5. Solution approach.

and ending kilometric points (best segments to be merged) according to homogeneous degradation level and close position. The output defines work zones of variable length, considering both maximum and minimum realistic length values based on the operational constraints of the infrastructure manager. The detailed pseudo-code of the algorithm is reported in Table 4. The algorithm is applied to a dataset ***df*** which includes the starting point, ending point, degradation score, and direction of each road segment.

The considered assumptions are:

- the maximum and minimum acceptable length of the work zones are given by the infrastructure manager;
- a degradation score is available for each road segment from a model for condition analysis;
- the position and considered direction for each road segment are known;
- the configuration of the road network is known and segments that belong to different highway stretches (between toll points) cannot be merged;
- other operational constraints that could limit the work zone length are neglected.

In detail, the merging algorithm consists of three main steps:

- **Step 1**: Initialisation. The structures to save the output data are defined and the maximum and minimum lengths for a work zone are set.
- **Step 2**: This step involves an iterative process based on a Sliding Window Technique (Ryang and Yun, 2016, [33]). In this algorithm, the technique is applied to try to merge each segment with the following one if the following conditions are satisfied:
  - two segments can be merged only if they belong to the same highway stretch (the stretch between two toll points) and in the same direction.
  - the total length must be lower than the maximum acceptable work zone length.
  - The standard deviation of the segments' degradation score must be within a given threshold.

Table 4
Pseudo code for merging algorithm.

Step 1. Initialisation	Let **merged_data = []** be an empty list to save the merged data. Define a helper function for segment lengths **segment_length (start, end): return end-start**
Step 2. Iterate Through the sections	define starting at index ***i*** = 0: 2.a. Initialise the variables through loops **2.a.1.while** *i* < *len(df)* start_index = *i* total_length = 0 scores = [] sum_scores = 0 sum_squares = 0 direction = df.iloc[start_index, 3] road_stretch_name = df.iloc[start_index, 5] end_index = start_index 2.b. Try to merge the subsequent segments using the *Sliding Window approach* **2.b.1. while** *end_index < len(df) and total_length ≤ max_length:* **2.b.2.** Retrieve the next segment's (*Start, End, degradation_score, Direction, and road_stretch_name)* **2.b.3. If** the *Direction* or *road_stretch_name* of the next segment is different from the current one, stop the merge **break** ***2.b.4.*** *proposed_length = total_length + segment_length (next_start, next_end)* **2.b.5. If** *proposed_length > max_length:* **break** 2.c. Update the constraint variables that is the *scores* and *lengths* to calculate the number of merged segments and their mean scores. Calculate the standard deviation and apply a check of merge-stopping. **2.c.1. If** Standard Deviation is Within Limits: Update *new_start = Start* (start of the first segment), *new_end = End* (end of the last merged segment). Append *[new_start, new_end,avg_degradation_score, Direction, road stretch_name]* to merged_data. **break** **2.c.2.** Move *i* to *end_index + 1* (move to the next unmerged segment). **2.c.3. If No Merge Happened**: *end_index == start_index), move i to the next segment (i + 1).*
Step 3. Adjusting Merged Segments	3.a. **If** there is any merged segment, adjust: Set the *Start* of the first segment to a fixed value Set the *End* of the last segment to a fixed value **End**

If these conditions are satisfied the merging is accepted and the next segment is considered.

- **Step 3**: Once the merging is completed, the proposed length is accepted and the starting and ending points of each merged work zone are saved, with the related average degradation score.

After merging the proposed work zones, the planning algorithm is applied to suggest the maintenance plan.

Regarding the planning algorithm, it is applied to the dataset **merged_data** which includes the work zone list generated by the merging algorithm, with the information of starting point, ending point, degradation score, and direction of each defined work zone.

The considered assumptions are:

- the position of each work zone is known;
- the information about traffic impact is known from the simulation results for each highway stretch (between toll points);
- the needed type of maintenance activity is suggested according to the degradation score, e.g. surface restoration in case of low pavement degradation and deep restoration in case of high degradation);
- the average maintenance duration is known according to the type of maintenance activity from historical data;

- Aggregated time intervals (e.g. months) are defined whose duration is expressed in days.

The planning algorithm consists of the following steps:

- **Step 1 initialisation**. Considering the merged segments obtained from the merging algorithm, set the number k of clusters to be considered and initialise the variables.
- **Step 2 clustering**. Apply the k-means clustering to the set of merged segments (work zones) identifying the barycentre of each cluster and the elements in each cluster according to the features degradation score and position.

Clustering is a key unsupervised learning technique. Its primary goal is to partition a dataset into distinct clusters, such that the data points within the same cluster exhibit higher similarity to each other compared to those in other clusters. $k-$means is a typical clustering algorithm in data mining that is widely used for clustering large data sets [34–36]. The method can classify the given data objects into k different clusters through an iterative process, converging to a local minimum. The algorithm consists of three separate phases. The first phase selects k centres (also called barycentres or centroids) randomly, where the value k is fixed in advance. The second phase consists of assigning each data object to the nearest centre. Euclidean distance is generally considered to determine the distance between each data object and the cluster's centres. When all the data objects are included in some clusters, the second phase is completed, and an early grouping is done. The third phase consists of recalculating the average of the early-formed clusters. This iterative process continues repeatedly until the criterion function minimum is reached. Supposing that the target object is x and x_i indicates the average of cluster C_i, the criterion function is defined as follows:

$$E = \sum_{i=1}^{k} \sum_{x \subset n_i} |x - x_i|^2 \tag{19}$$

E is the sum of the squared error of all objects in the database. The distance of the criterion function is the Euclidean distance, which is used for determining the nearest distance between each data object and cluster centre. After applying the k-means clustering tool to the merged dataset, the data are partitioned into distinct clusters. Additionally, the barycentre for each cluster is provided.

- **Step 3**. Input data about duration and traffic information are defined for each merged work zone and each barycentre. The duration is set according to the degradation score and the related type of maintenance activity, while the traffic information depends on the highway stretch (between two toll points) to which the merged segments (work zone) belong.
- **Step 4: barycentres ordering**. Each barycentre is treated as a fictitious work zone, representing the average characteristics of its corresponding cluster, in terms of position and degradation score. To order these fictitious work zones, *aggregated time intervals* are defined, with duration (expressed in days) at least equal to the sum of the durations of the maintenance activities/work zones that belong to that cluster. For each aggregated time interval, the traffic flow is estimated as the average of the daily traffic volumes. Regarding the work zone configurations of the fictitious work zones, they are assumed to have the same impact on traffic, assuming an average value of the queue length and travel time delay, as the focus in this step is on determining the optimal sequence of the fictitious work zones, but not on their configurations. Taking into account these simplifications, each barycentre is treated as a single maintenance intervention, and the optimisation model described in Section 3.3 is applied to the set of fictitious work zones. The output is an optimal sequence of clusters, each assigned to a specific aggregated time interval (e.g. month).
- **Step 5: clusters planning**. The complete optimisation model described in Section 3.3, is applied to the elements (work zones) of each cluster, separately.
- **Step 6: yearly plan and computation of objective function terms**. The plans of each cluster are merged according to their barycentres order and the values of the objective function terms are computed.

Table 5
Pseudo code for planning algorithm.

Step 1. Initialisation	Get **merged_data,** the work zone list generated by the merging algorithm, which includes [start, end, avg_degradation_score, Direction, road_stretch_name]. Define the number of clusters $k = n$
Step 2. Clustering	Apply k-means algorithm **2.1.** define k_means_cluster(k, points) **2.2** Select k barycentres randomly barycentres= [c1, c2, …, ck] Repeat until convergence: **2.3** Assign each point to the "closest" barycentre For each data point in merged_data: Calculate the distance between the data point and each barycentre. Assign the data point to the nearest barycentre. **2.4** Update step For each barycentre: Calculate the new barycentre by taking the mean of all data points assigned to it **2.5** Convergence criteria: Check if the barycentre has stopped moving (i.e., the changes in barycentre positions are below a certain threshold). If barycentres have converged, save barycentres and terminate the algorithm. If not, repeat steps 2.a.3 and 2.a.4
Step 3. Input data generation	For each point in merged_data and in barycentres: **3.1** Check the highway section (road_stretch_name) set the traffic information from the simulation results **3.2** Check the degradation score (avg_degradation_score) set the type of activity according to the degradation score set the duration according to the type of activity end
Step 4. Barycentres ordering	Considering the elements in barycentres: Minimise the objective function of Eq.(8) Subject to constraints (9–18) Save barycentre_order
Step 5. Clusters planning	Plan each cluster separately according to barycentre_order **5.1** Read the position p of cluster i in barycentre_order **5.2** For $p = 1 : k$ Plan the cluster in position p minimizing the objective function of Eq. (8) Subject to constraints (9–18) end **5.3** save cluster_plan and objectives values (obj with $j = 1..m$)
Step 6 yearly plan and objective function terms computation	**6.1** Merge the cluster plan to obtain the yearly plan For $p = 1 : k$ t_start of the plan of the cluster in position p = (t_end of the plan of the cluster in position $p - 1$) + 1 end save yearly plan **6.2** For $p = 1 : k$ Considering the objectives obj of each cluster plan to get the objective function terms of the yearly plan. end Save the objective function terms

In Table 5, the pseudo-code of the proposed planning algorithm is presented.

To evaluate the computational efficiency and the performance of the proposed algorithm, the approach is tested with different instances of the problem and the gap concerning the optimal solution, computed by a commercial solver, is reported.

Fig. 6 demonstrates the significant improvement in computational performance achieved through the application of the proposed solution algorithm. As mentioned in Figure, the commercial solver is not able to solve large instances, such as the scheduling of 60 work zones over a 365-day horizon, therefore only smaller instances are tested to compare the optimal results from the commercial solver and the results obtained with the proposed algorithm. The proposed solution algorithm effectively decomposes the problem into smaller, more manageable subproblems, reducing significantly the computational time across all instance sizes, while keeping consistently high the quality of the solution. Notably, the algorithm computes the optimum (same results as the CPLEX solver) for instances of sizes 15, 20, and 25 work zones. For larger instances, the gap concerning the optimum remains small, 3.8 % for instance of 30 work zones, 5 % for instance of 45 work zones, and 6.9 % for instance of 55 work zones. The total computational time considering the instance of 55 work zones is 49 s, compared to 8201 s of the commercial solver. It makes the proposed approach practical for yearly maintenance planning without compromising computational efficiency. Table 6 provides a detailed breakdown of the computational time for each step of the solution algorithm. It highlights the contributions of individual steps to the overall performance enhancement.

5. Model applicability and transferability

Regarding the real-world implementation challenges, it is worth highlighting that the proposed tool has been integrated into a Decision Support System (DSS) platform within the Horizon 2020 OMICRON project. In doing that, the first identified challenge is the interconnection of the platform with the infrastructure managers' existing asset management systems. To address this issue, the JSON (JavaScript Object Notation) data format was chosen for the interconnection, which is easy to integrate across different systems and technologies since it is flexible and widely supported. In addition, a dedicated Application Programming Interface (API) was designed to be modular, allowing for adaptability and easy modification.

Table 6
Solution algorithm computational time for a large instance of 100 work zones.

No.	Algorithm step	Average time (s)
1	Merging the interventions	2.34
2	Work zone clustering	2.51
3	Input data generation	5.12
4	barycentres ordering	3.3
5	Cluster planning	35.8
	Total	49.07

Concerning the transferability of the approach for pavement analysis, a widely recognised performance indicator, GPI, was utilised according to the Europe COST Action 354 [32]. The considered GPI is a harmonizing performance indicator for road pavement management across Europe, developed to promote technical collaboration among countries in the field of pavement management and is easily adaptable to different roads.

The pavement condition algorithm can incorporate new road pavement data and train the model accordingly. The raw results from the algorithm are provided for each data point of inspection location, without being constrained by specific road manager's segmentation rules. Then, the elaboration of the raw results can be performed according to the segmentation criterion requested by the specific application.

Therefore, the segmentation methodology can be easily adapted to meet the specific infrastructure managers' needs or rules.

The traffic simulation can be adapted to highway sections with different geometric characteristics such as the number and width of lanes and different work zone configurations (starting and ending point, number of closed lanes, number of diverged lanes, traffic directions, etc.). In addition, the speed limitations and traffic rules, specific to each country or case study, can be implemented as parameters in the simulator. Specific traffic data can be used as inputs, considering the traffic composition and the traffic demand of the case study to be tested.

Regarding the general applicability of the planning model, the proposed approach can be applied to different highway networks and case studies thanks to the general characteristics of its input data and parameters. In particular, the optimisation model can use degradation inputs from different data-driven models for condition analysis,

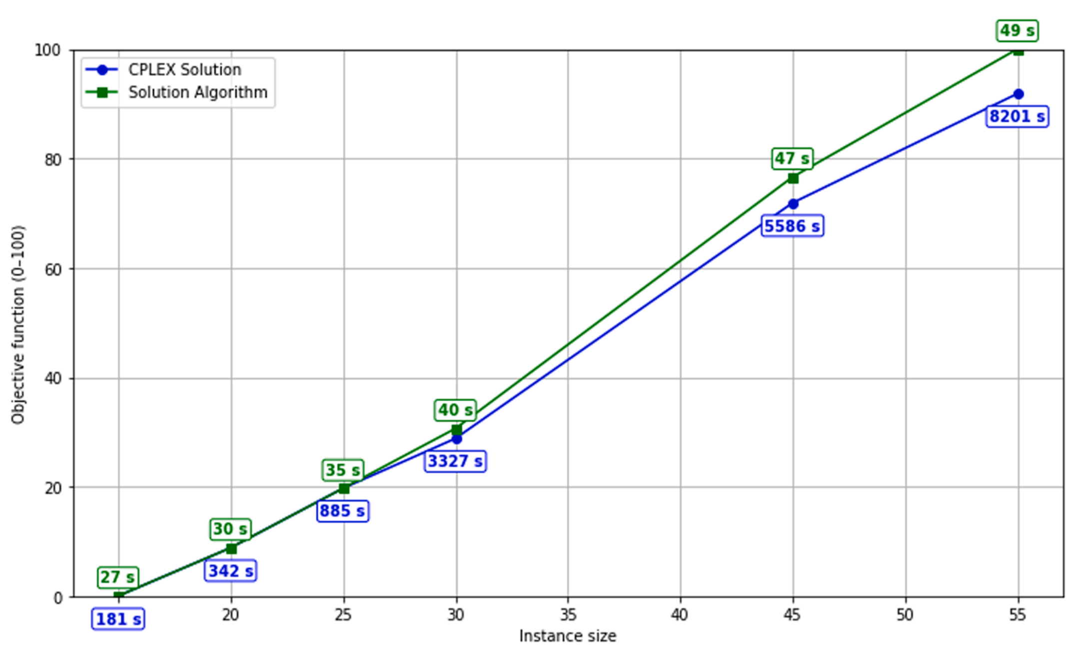

Fig. 6. Performance of solution algorithm with varying instance sizes.

according to the considered assets and available data. The merging algorithm can be adapted to the maximum and minimum work zone length considered by the infrastructure manager. Therefore, the proposed methodologies are developed to allow for generalization and scalability to accommodate new data, scenarios, and future projects, ensuring adaptability and effectiveness across different contexts.

The second challenge that, if addressed, could facilitate the applicability and transferability of the approach, is the standardisation of the Decision Support System for highway maintenance planning. To move towards the standardisation, a CEN Workshop Agreement (CWA) (CWA 18,176:2025) [37] has been published. It describes the main functionalities, features, information workflow, and elements of the DSS systems for highway maintenance planning, proposing some guidelines for its implementation.

Finally, a market analysis was performed within the OMICRON project identifying the customer segments reported in Table 7, their needs, and goals in the application of the proposed solution.

6. Case study

To validate the proposed approach, a real-world case study was conducted, within the final demonstrator of the OMICRON Horizon 2020 project, on a section of an Italian highway network. This network is one of the busiest in the country, linking several major cities and experiencing significant traffic congestion, particularly during peak demand and holidays. The highway network extends over approximately 750 km, with the 60-km length under study serving traffic in both directions and connecting several toll points. However, following the project confidentiality rules, the specific name of the highway cannot be disclosed.

The considered 60 km are split into two branches: an older route and a newer one, the latter constructed in recent years to accommodate increasing traffic demand. These two routes merge and diverge at multiple points, featuring both shared and exclusive toll gates. It includes multiple lanes in each direction, typically ranging from two to four lanes, although the extent of the four-lane segments is not considered significant for the analysis. All maintenance and traffic data provided by the highway administration have been anonymized to ensure confidentiality. The studied highway network is shown in Fig. 7.

The studied area has undergone various pavement maintenance activities. A detailed summary of the types and frequencies of these activities over two years is presented in Table 8. It provides a comprehensive overview of the pavement maintenance activities.

In the simulation phase, the microsimulation software PTV VISSIM® is utilised to model and analyse traffic behaviour. As previously stated, the examined metrics include the average maximum queue length $\overline{q}_{i,n_i}^{M}$ and the average delay time $\overline{ad}_{i,n_i}$. These metrics are assessed for the two considered configurations (one-lane closure and traffic deviation) in all the highway stretches (between toll points) to evaluate and compare the impacts on traffic.

The optimisation model is tested and validated using outputs from the simulation, the pavement condition analysis, and detailed maintenance data provided by the road administration. In particular, from the pavement condition analysis, the degradation level is derived, while the infrastructure manager's dataset provides the maintenance duration for various configurations and includes critical information such as maintenance priority, and deadline requirements for each work zone. The optimisation problem is solved by applying the proposed solution algorithm, developed using Python and the commercial solver IBM-Ilog CPLEX® (version 22.11), executed on a system with a 2.30 GHz processor and 16 GB of RAM. In this case study, the considered time interval is the day, whereas the month is assumed as the aggregated time interval used by the algorithm, defined in Section 4. Furthermore, Table 9 provides a comprehensive summary of the key characteristics and features of the work zones within the analysed network.

7. Results

In this section, the results of the study are presented. The pavement analysis results indicate the degradation level of each highway segment, the traffic simulation results provide critical insights into the behaviour of traffic under various work zone configurations, while the planning results demonstrate the practical applicability of the approach in formulating effective maintenance schedules.

7.1. Pavement analysis results

The results from the different approaches and models, described in Section 3.1 are summarised in Tables 10–15 which show the results of each model for each specific approach. The results show that the Random Forest model provides in all cases the best results. In addition, to select the most appropriate approach in applying the Random Forest, the Mean absolute Percentage errors of each approach are compared in Table 15, showing that the approach that provides the best results is the use of degradation data with time dimension, obtaining a mean absolute percentage error of 5.6 %.

A visualization of the pavement results showing the different road segments with a colour relative to the different degradation levels is shown in Fig. 8. A box shows the specific parameters calculated per road segment, which are detailed in the figure on the right. This box shows the initial and final kilometric point position of the segments, their direction, the predicted values of IRI, TEX, and SFC, the comfort and safety indicators calculated based on the prediction, the global condition parameter, and the label which shows qualitatively the meaning of this global parameter value.

7.2. Simulation results

The simulation of various scenarios provided key service level parameters for different work zone configurations. Specifically, the analysis focused on evaluating queue lengths and travel time delays across two distinct work zone configurations (lane closure (in yellow) and traffic deviation (in red)) within each relevant highway segment (between toll points). The results of the simulation for a single work zone

Table 7
Customer segments of the DSS market.

Customer segment	Role	Needs	What can be improved	Purchase decision
Public authorities	Responsible for overseeing the maintenance of highway infrastructure.	Ensure reliable maintenance management of aging highway infrastructure.	Improving decision-making and planning processes Streamlining management processes	Monetary (based on tenders)
Concessionaires	Contracted by authorities to manage specific infrastructure assets.	Minimize operational disruptions and costs.	Optimisation of resource allocation Greater visibility and understanding of infrastructure data	Saving costs, quality of the service
Asset managers	Involved in the maintenance and management of highway infrastructure.	Minimize operational disruptions and costs.	Enhancing safety Increasing efficiency and effectiveness of maintenance tasks	Saving costs, quality of the service

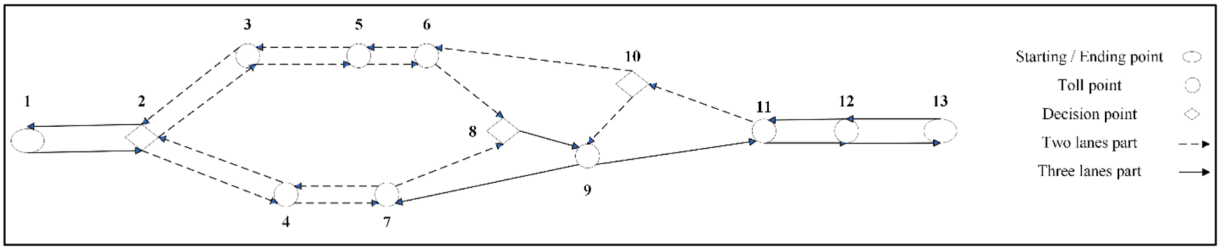

Fig. 7. The studied highway network.

Table 8
Pavement maintenance in the studied area.

No.	Pavement type	Frequency
1	Pavement deep restoration + draining	76
2	Pavement restoration	46
3	Pavement surface	23
4	Pavement other works	16
5	Drainage pavement	15
6	Pavement patching	6
7	Pavement roughening	2
	All the pavement interventions	184

are depicted in Fig. 9(a) and (b). These figures illustrate and compare the impact of each configuration on traffic flow. By highlighting the strengths and weaknesses of each configuration, the analysis provides insights into optimising traffic management strategies to enhance highway efficiency during maintenance activities.

Table 16 presents a summary of the simulation results for various work zone configurations applied to different highway sections. This table provides a detailed comparison of the effects of each configuration on traffic flow, enabling a better understanding of their respective impacts. The data outlined in Table 16 serves as input parameters for the subsequent mathematical modelling process.

7.3. Planning results

The proposed mathematical model integrates work zone characteristics with key level-of-service parameters. This approach helps to prioritise maintenance activities more effectively by considering both pavement conditions and traffic disruptions, generating insights to support decision-making.

To assign different clusters to specific months, two scenarios were considered: a degradation-based scenario and a combined (degradation and traffic-based) scenario. In this study, both scenarios are utilized to demonstrate and compare their outcomes in the context of yearly planning concerning historical pavement maintenance data.

In the degradation-based scenario, the ordering of clusters and their assignment to specific months is determined according to the average degradation level of each cluster. Clusters with higher average degradation levels are prioritised and assigned to the initial months of the year, while those with lower average degradation levels are postponed to the next months. The results of cluster ordering and assignment in the degradation-based scenario are presented in Fig. 10. The values displayed on each bar of the Gantt chart represent the average degradation level of the corresponding cluster. In this scenario, the primary

Table 10
Evaluation results using all data with data from the same year.

Error\Model	Baseline	Linear Regression	Decision Tree	Random Forest
Mean Squared Error	0.328	0.162	0.252	0.132
Mean Absolute Percentage Error	0.257	0.163	0.197	0.147
Median Absolute Error	0.390	0.208	0.254	0.185
Max Error	3.053	2.046	2.333	1.957

Table 11
Evaluation results using all data without data from the same year.

Error\Model	Baseline	Linear Regression	Decision Tree	Random Forest
Mean Squared Error	0.328	0.162	0.247	0.134
Mean Absolute Percentage Error	0.257	0.163	0.193	0.150
Median Absolute Error	0.390	0.210	0.250	0.188
Max Error	3.053	2.041	2.333	1.923

Table 12
Evaluation results using only degradation data without time dimension.

Error\Model	Baseline	Linear Regression	Decision Tree	Random Forest
Mean Squared Error	0.271	0.0736	0.086	0.0633
Mean Absolute Percentage Error	0.278	0.127	0.126	0.108
Median Absolute Error	0.362	0.153	0.137	0.111
Max Error	1.288	0.993	1.027	0.806

Table 9
Example of the work zone features.

Work zone	Section	Conf 1 (C1)	Conf2 (C2)	Duration C1 (day)	Duration C2 (day)	Queue length C1 (km)	Queue length C2 (km)	Delay C1 (min)	Delay C2 (min)	Section Ranking	Degradation level	Priority	Deadline
Wz 1	Section 3	LC*	CD**	1	1	0.98	3.26	6.43	24.96	4	7	2	10
Wz 2	Section 8	LC	CD	2	1	1.12	8.04	7.46	53.92	7	6	1	18
…	…	…	…	…	…							…	…
Wz 90	Section 6	LC	CD	2	1	1.03	4.19	7.36	26.97	6	10	1	12

* Lane closure.
** Carriageway deviation.

Table 13
Evaluation results using only degradation data with time dimension.

Error\Model	Baseline	Linear Regression	Decision Tree	Random Forest
Mean Squared Error	0.305	0.091	0.055	0.029
Mean Absolute Percentage Error	0.314	0.147	0.056	0.056
Median Absolute Error	0.443	0.174	0.164	0.025
Max Error	1.588	1.367	1.785	1.366

Table 14
Using all data adding maintenance parameter.

Error\Model	Baseline	Linear Regression	Decision Tree	Random Forest
Mean Squared Error	0.288	0.056	0.0976	0.053
Mean Absolute Percentage Error	0.285	0.103	0.121	0.098
Median Absolute Error	0.355	0.145	0.126	0.122
Max Error	1.392	0.727	1.122	0.585

Table 15
Using all data adding maintenance parameter.

Approach	Mean absolute percentage error [%]
Using all data with data from the same year	14.7
All data without data from the same year	15
Only degradation data without a time dimension	10.8
Only degradation data with time dimension	5.6
Using all data adding maintenance parameter	9.8

objective in cluster order is to address maintenance needs according to the pavement condition analysis without considering traffic information.

In the combined scenario, clusters are assigned to specific months based not only on the degradation level but also on the traffic disruption each cluster causes, considering the average traffic flow of the road sections during different months. The model aims to assign the cluster with the highest traffic disruption to the month with the lowest average traffic flow. The results of cluster assignment under the combined scenario are illustrated in Fig. 11. In this scenario, the primary aim of the model in cluster order is to minimise traffic disruptions while ensuring the satisfaction of maintenance needs.

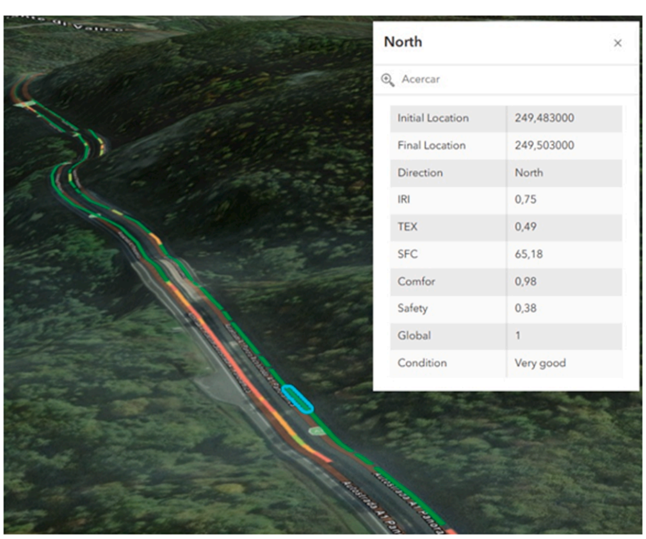

Fig. 8. Results of pavement condition analysis.

To assess the results, the yearly plans created for both scenarios, according to the solution algorithm reported in Section 4, are compared with historical pavement data. The historical data represent the maintenance plans executed by the infrastructure managers in the past year regarding pavement interventions. The performance of the executed plans is computed by imposing the historic maintenance plan as input in the calculation of the objective function in Eq. (8).

Fig. 12 visually represents this comparison considering the terms of the objective function from Eq. (8). In more detail:

- Queue is computed according to the first term in Eq. (8) and represents the impact on traffic in terms of traffic queue length due to the considered work zone configurations.
- Delay, from the second term in Eq. (8), represents the impact on traffic in terms of travel time delay due to the considered work zone configurations.
- Traffic impact derives from the third term in Eq. (8) which represents the impact on traffic taking into account the traffic volume variability among the different days, that is, the cost of planning work zones during the peak days.
- Priority, computed according to the fourth term in Eq. (8) represents the cost of postponing an activity with high priority.
- Degradation, fifth term in Eq. (8), which represents the cost of postponing an activity with high degradation.

Fig. 12 highlights that the combined scenario guarantees the best performance in terms of minimization of traffic disruption, including queue length, delay, and traffic impact. However, concerning maintenance needs in terms of priority and degradation, its performance is in between the historic data scenario and the degradation-based scenario. In detail, the combined scenario performs 8 % better than historic data in reducing queue and delay, 22 % better in traffic impact, 41 % better in priority, and 8 % better in degradation. This highlights its superior performance across all five objective terms compared to the historical data. On the other hand, the degradation-based scenario stands out as the best option for meeting maintenance needs, including priority and degradation. It performs 50 % better than the historical data in priority and 22 % better in degradation. Compared to the combined scenario, it achieves a 9 % improvement in priority and a 14 % improvement in degradation, while it performs worse with regards to traffic (+ 38 % in terms of queue and delay and + 9 % in terms of traffic peak impact).

For the sake of space limitation, a single case is presented to illustrate the results of monthly cluster planning, that is, the Gantt charts for all clusters are not included. The detailed operational schedule of work zones within Cluster 7 is presented in Fig. 13, which represents the July maintenance plan since Cluster 7 is assigned to July, as shown in Fig. 10.

Fig. 13 presents a Gantt chart where the y-axis indicates the road section and the direction for each work zone and the x-axis indicates the days of the month. The Gantt shows that all the work zones in this cluster are implemented under a lane closure configuration (depicted in blue colour), as it has a lower impact on traffic. The completion of activities for cluster 7 required 30 days. Notably, there were no active work zones on days 8, 9, 15, 16, and 23.

To understand the reasoning behind this scheduling pattern, it is necessary to consider the traffic data for July. Fig. 14 presents a heatmap of traffic flow across various road sections during July. In the heatmap, colours indicate the level of traffic flow, ranging from light blue (lowest flow) to dark red (highest flow) in each section. The heatmap highlights that days 9, 16, and 23 are peak days for the road sections under maintenance (Sections 5 and 7) within this cluster during the observed period. Therefore, to minimize traffic disruptions, the model excludes these days from the maintenance schedule (no work zones are planned during these days).

A sensitivity analysis was conducted to evaluate the impact of varying emphasis on traffic disruptions and maintenance needs by adjusting the weight μ in the objective function (Eq.(8)) of the optimi-

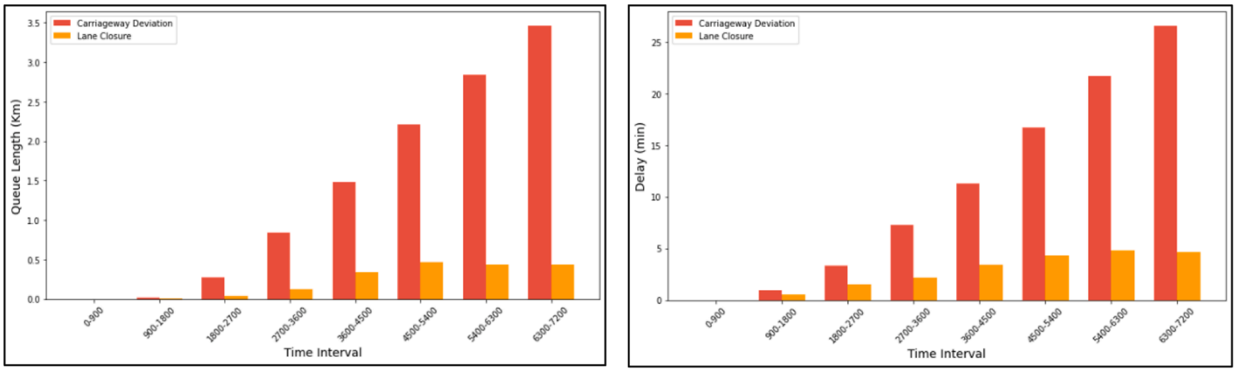

Fig. 9. (a) – Queue length in different configurations, (b) Travel time delay in different configurations.

Table 16
Simulation results.

Section	Direction	Lane closure		Carriageway deviation	
		Average queue length (Km)	Avenge travel time delay (min)	Average queue length (Km)	Avenge travel time delay (min)
Section 1	North	1.09	6.14	4.57	28.89
	South	1.47	8.16	5.11	33.47
Section 2	North	0.98	6.43	3.26	24.96
	South	1.05	7.45	3.82	26.39
Section 3	North	0.72	4.95	3.95	26.89
	South	0.89	5.21	4.16	26.96
Section 4	North	0.93	6.32	4.27	28.61
	South	0.63	4.04	3.46	25.57
Section 5	North	1.03	7.36	4.19	26.97
	South	1.19	8.24	8.55	58.72
Section 6	North	1.97	12.71	6.71	45.33
	South	1.12	7.46	8.04	53.92
Section 7	North	1.97	12.71	6.71	45.33
	South	1.12	7.46	8.04	53.92
Section 8	North	1.01	6.97	7.37	50.21
	South	1.43	8.74	9.11	61.09
Section 9	North	1.01	6.97	7.37	50.21
	South	1.43	8.74	9.11	61.09

sation model presented in Section 3.3. As shown in Fig. 15, when $\mu = 0.1$, the model prioritises maintenance needs, whereas, at $\mu = 0.9$, the focus shifts toward minimizing traffic disruptions. At $\mu = 0.5$, a balanced approach is achieved, giving equal consideration to traffic disruptions and maintenance needs.

8. Conclusions

This study introduces a novel framework for optimising maintenance work zone management on highway networks to reduce traffic disruptions while ensuring effective pavement maintenance. The proposed methodology combines traffic simulations, pavement condition analysis, and a maintenance planning optimisation model to address the challenge of balancing maintenance needs with traffic flow optimisation.

Applied to a case study on an Italian highway network, the methodology demonstrated significant improvements in both traffic performance and maintenance planning. The findings highlight the benefits of aligning road degradation priorities with traffic impacts, offering a comprehensive solution for pavement maintenance on busy highway networks. The integration of traffic microsimulation tools and machine learning techniques enhances decision-making processes, paving the way for scalable and data-driven approaches. Furthermore, the proposed merging and planning algorithms provide practical solutions for large-scale networks, overcoming computational limitations.

Concerning the study limitations, real-world data or field measurements could not be used to validate the traffic impact results since this would have needed the implementation of the proposed maintenance plan and a long period of observation and data collection. However, the obtained results have been compared with the real maintenance plan already executed by the highway infrastructure manager and the traffic simulation model has been calibrated according to the real traffic data.

Regarding the traffic demand variation, since the study deals with the mid-term planning, the model considers only traffic flow fluctuations between the different days of the month neglecting long-term factors, such as modification in local transport policies or socio-

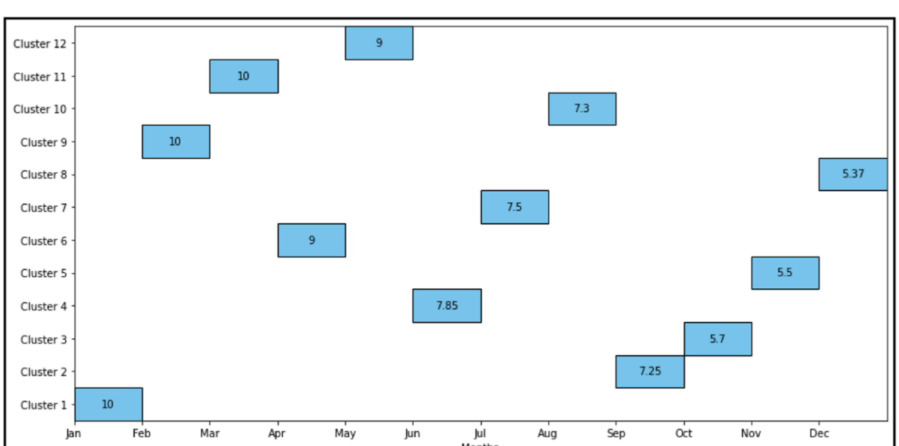

Fig. 10. Clusters ordering in degradation-based scenario.

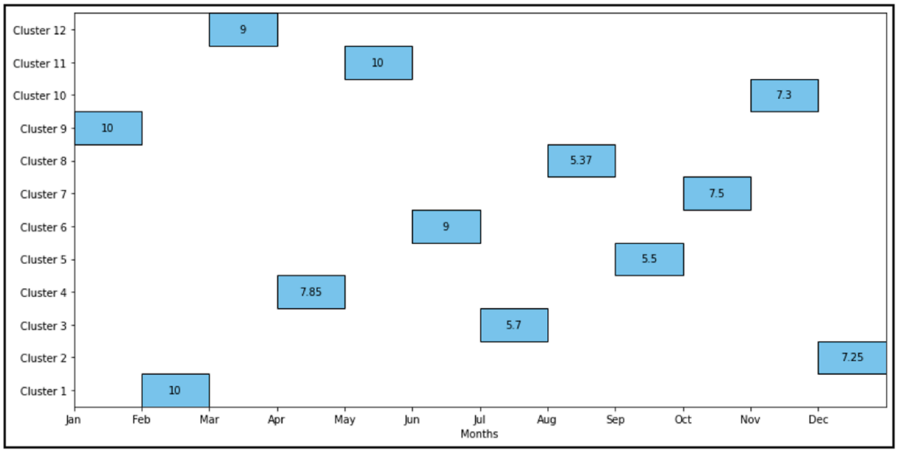

Fig. 11. Clusters ordering in combined scenario.

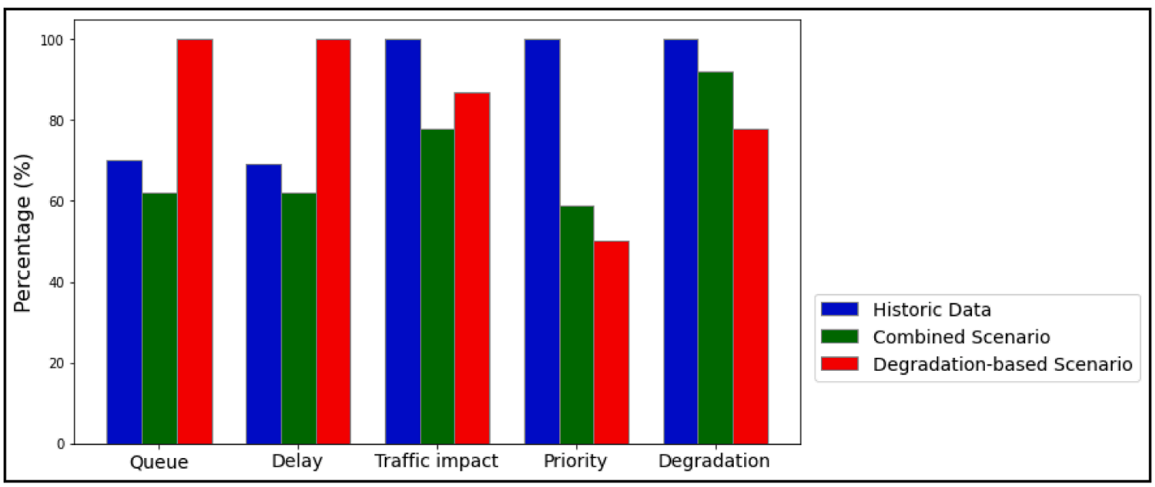

Fig. 12. Objective terms comparison for a different yearly plan.

economic factors, which could influence the traffic demand in the long-term. Therefore, in the proposed model, it is assumed that no significant modifications in terms of regional/local policies or socioeconomic events are going to occur during the considered time horizon of one year. However, to enhance the proposed approach the integration with a mid-term prediction model to forecast possible transport demand peaks, such as the one proposed by Belt et al. [38], could be addressed in the future if enough traffic data is available to develop, calibrate, and test the model. Instead, the integration with a long-term prediction model of transport demand is out of the scope of this research, since long-term prediction models apply to strategic maintenance planning, characterised by a longer time horizon, and are used to improve the understanding of maintenance strategies' long-term impacts.

Another limitation regards the estimation of maintenance costs. The

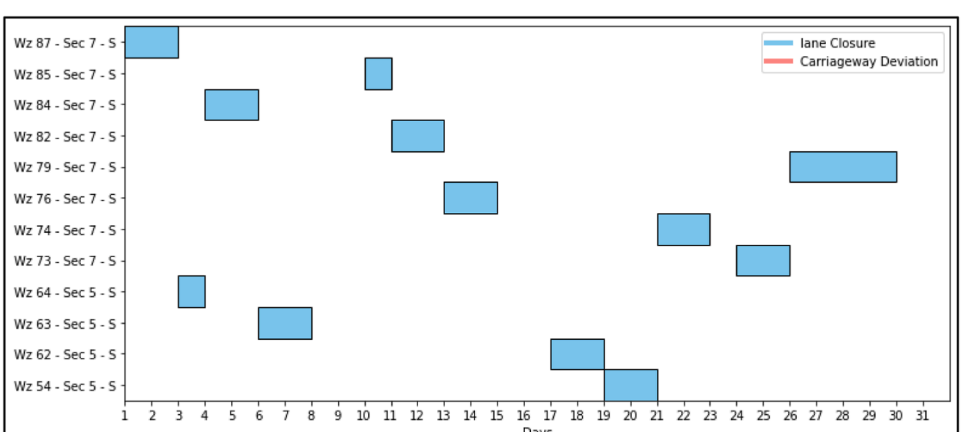

Fig. 13. Gantt chart of pavement activities in July.

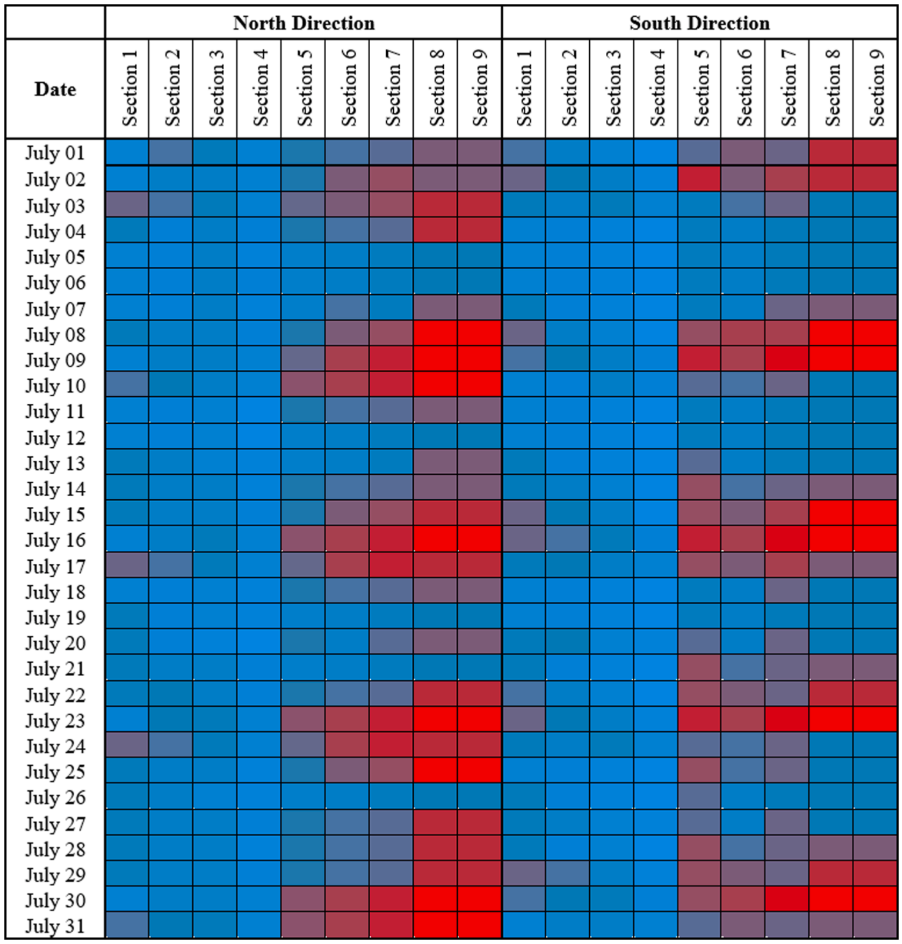

Fig. 14. Heatmap of traffic flow in different road sections in July.

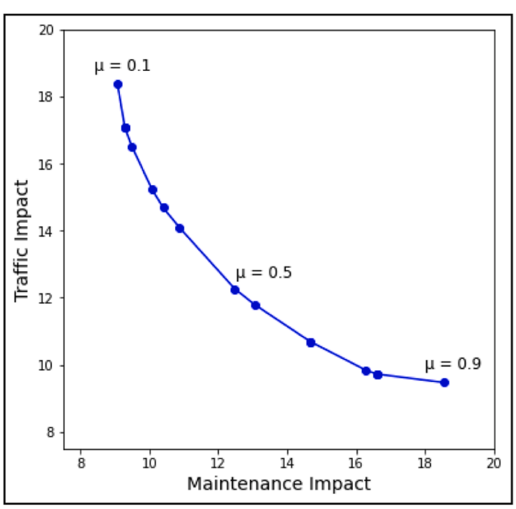

Fig. 15. Sensitivity analysis.

data about the cost of maintenance plan execution were not shared by the infrastructure manager due to their sensitivity. This does not allow for a detailed comparison from the economic point of view. However, assuming higher costs of maintenance execution on pavement segments characterised by a higher degradation, a reduction of 30 % has been estimated with the proposed approach by applying predictive maintenance strategies, and executing maintenance on road sections before they reach a highly degraded condition.

From the societal impact point of view, the unavailability of data about road accidents, not disclosed by the infrastructure manager due to their sensitivity, have prevented from conducting a detailed analysis about risk reduction. However, the application of user-oriented predictive maintenance strategies can reduce the road hazard risk before and during maintenance execution. Before the maintenance execution, a predictive maintenance plan limits the road segments that reach highly degraded conditions which may lead to accidents, while during maintenance, user-oriented strategies reduce the exposure, that is, the traffic volumes involved during the presence of the work zone, which may increase the probability of vehicle collisions due to the change in the carriageway geometry.

Regarding possible barriers to the adoption of the proposed approach, specific constraints for the infrastructure managers may exist in terms of contractual requirements, budget limitations, operational and logistics constraints, and highway network topology and structure. However, they are usually known in advance and can be introduced in the model as additional mathematical constraints.

As mentioned, during the maintenance plan execution, deviations from the proposed plan are expected due to unexpected events such as weather conditions, or maintenance teams or equipment unavailability. These aspects are dealt with at the operational level through a dynamic replanning approach which is out of the scope of this work. However, the average weather conditions in the different months of the year can be taken into account in the future developments of the solution algorithm introducing a refinement step of clustering planning. This refinement step can include a constraint related to the maximum number of maintenance interventions that can be planned during a month characterised by a high average number of rainy days, considering also possible future variation in precipitation patterns due to the climate change effects. In the considered case study, the number of maintenance activities executed in the past during the different months of the year have been analysed to check the months characterised by the highest number of executed work zones. However, due to the high variability and uncertainty of weather conditions, it has been considered preferable to deal with this aspect at an operational level.

Finally, future research can incorporate stochastic maintenance variables, such as stochastic completion times, to further improve the overall performance of the proposed methodology.

CRediT authorship contribution statement

Mohammad Abbasi: Visualization, Software, Writing – original draft, Validation, Methodology. **Muhammad Tabish Bilal:** Writing – original draft, Software, Conceptualization, Writing – review & editing, Validation, Methodology. **Alice Consilvio:** Writing – original draft, Supervision, Methodology, Conceptualization, Writing – review & editing, Validation, Project administration, Funding acquisition. **Davide Giglio:** Writing – review & editing. **Nicola Sacco:** Writing – review & editing, Conceptualization. **Paula Lopez Arevalo:** Software, Methodology, Writing – review & editing, Resources, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 955269.

Data availability

The data that has been used is confidential.

References

[1] K. Heng, R. Li, Z. Li, H. Wu, Dynamic responses of highway bridge subjected to heavy truck impact, Eng. Struct. 232 (2021) 111828.
[2] S. Fallah-Fini, K. Triantis, La De, J.M. Garza, W.L. Seaver, Measuring the efficiency of highway maintenance contracting strategies: a bootstrapped non-parametric meta-frontier approach, Eur. J. Oper. Res. 219 (2012) 134–145.
[3] J. France-Mensah, C. Kothari, W.J. O'brien, J. Jiao, Integrating social equity in highway maintenance and rehabilitation programming: a quantitative approach, Sustain. Cities. Soc. 48 (2019) 101526.
[4] A. Consilvio, L. Calabro, A. Di Febbraro, N. Sacco, A multimodal solution approach for mitigating the impact of planned maintenance on metro rail attractiveness, EURO J. Transp. Logist. 10 (2021) 100047.
[5] A. Consilvio, G. Vignola, P. Lopez Arevalo, F. Gallo, M. Borinato, C. Crovetto, A data-driven prioritisation framework to mitigate maintenance impact on passengers during metro line operation, Eur. Transport Res. Rev. 16 (2024) 6.
[6] Y. Yu, J. Weng, W. Zhu, Optimizing strategies for the urban work zone with time window constraints, Sustainability 11 (2019) 4218.
[7] M. Abi Aad, M. Abbas, An optimization framework for pavement treatment and spatio-temporal distribution of work zone closures, Transp. Res. Procedia 82 (2025) 3096–3109.
[8] H. De Medeiros Pereira, J.E.B. Junior, R.A. De Albuquerque Nobrega, Geospatial-based decision support system for prioritizing road segments for maintenance and rehabilitation, Case Stud. Transp. Policy 16 (2024) 101170.
[9] R. Shah, O. Mcmann, F. Borthwick, Challenges and prospects of applying asset management principles to highway maintenance: a case study of the UK, Transp. Res. Part A 97 (2017) 231–243.
[10] K.F. Tee, E. Ekpiwhre, Strategic cost modelling and optimisation for highway asset maintenance, J. Qual. Maint. Eng. 26 (2020) 198–212.
[11] J. Li, G. Yin, X. Wang, W. Yan, Automated decision making in highway pavement preventive maintenance based on deep learning, Autom. Constr. 135 (2022) 104111.
[12] C. Han, T. Ma, G. Xu, S. Chen, R. Huang, Intelligent decision model of road maintenance based on improved weight random forest algorithm, Int. J. Pavement Eng. 23 (2020) 985–997.
[13] C. Han, T. Ma, S. Chen, Asphalt pavement maintenance plans intelligent decision model based on reinforcement learning algorithm, Constr. Build. Mater. 299 (2021) 124278.
[14] M. Pourgholamali, S. Labi, K.C. Sinha, Multi-objective optimization in highway pavement maintenance and rehabilitation project selection and scheduling: a state-of-the-art review, J. Road Eng. (2023).
[15] L. Cao, T. Tan, X. Hou, Z. Dong, Decision-making optimization model for the targeted sustainable maintenance of a complex road network, J. Clean. Prod. 434 (2024) 139891.
[16] H. Naseri, A. Aliakbari, M.A. Javadian, A. Aliakbari, E. Waygood, A novel technique for multi-objective sustainable decisions for pavement maintenance and rehabilitation, Case Stud. Constr. Mater. 20 (2024) e03037.
[17] F. Borghetti, G. Beretta, N. Bongiorno, M. De Padova, Road infrastructure maintenance: operative method for interventions' ranking, Transp. Res. Interdiscip. Perspect. 25 (2024) 101100.
[18] V. Donev, M. Hoffmann, Optimisation of pavement maintenance and rehabilitation activities, timing, and work zones for short survey sections and multiple distress types, Int. J. Pavement Eng. 21 (2020) 583–607.
[19] K. Sasai, L.E. Chouinard, G.J. Power, D. Conciatori, N. Zufferey, Accounting for traffic disturbance in road infrastructure management: optimal maintenance and rehabilitation planning for the society, Transp. Res. Part A 183 (2024) 104040.
[20] M. Abbasi, M.T. Bilal, A. Consilvio, D. Giglio, On planning highway maintenance considering the impact on traffic flow due to different work zone configurations, Transp. Res. Procedia 86 (2025) 508–515.
[21] J. Hang, X. Yan, L. Ma, K. Duan, Y. Zhang, Exploring the effects of the location of the lane-end sign and traffic volume on multistage lane-changing behaviors in work zone areas: a driving simulator-based study, Transp. Res. Part Fr 58 (2018) 980–993.
[22] N. Raju, S. Arkatkar, G. Joshi, Effect of construction work zone on traffic stream parameters using vehicular trajectory data under mixed traffic conditions, J. Transp. Eng. Part A 146 (2020) 05020002.
[23] T. Saha, V.P. Sisiopiku, Assessing work zone traffic control options for 3-to-1 lane closures, J. Transp. Technol. 10 (2020) 50.
[24] J. Bae, K. Choi, J.H. Oh, Multicontextual machine-learning approach to modeling traffic impact of urban highway work zones, Transp. Res. Rec. 2645 (2017) 184–194.
[25] M.M. Mekker, Y.-J. Lin, M.K. Elbahnasawy, T.S. Shamseldin, H. Li, A.F. Habib, D. M. Bullock, Application of LiDAR and connected vehicle data to evaluate the impact of work zone geometry on freeway traffic operations, Transp. Res. Rec. 2672 (2018) 1–13.
[26] N. Bharadwaj, P. Edara, C. Sun, H. Brown, Y. Chang, Traffic flow modeling of diverse work zone activities, Transp. Res. Rec. 2672 (2018) 23–34.
[27] M. Van Aerde, Single regime speed-flow-density relationship for congested and uncongested highways, in: 74th Annual Meeting of the Transportation Research Board, Washington, DC, 1995.
[28] F. Silvestri, A. Polimeni, O. Belcore, Impact mitigation of tunnels maintenance works on highway performance, Procedia Struct. Integrity 62 (2024) 998–1005.
[29] A.T.U. Chy, V.P. Sisiopiku, Quantifying operational impacts of variations in work zone setups, traffic demand, and traffic composition: a case study, J. Transp. Technol. 13 (2023) 18–37.
[30] H. Ge, Y. Yang, Research on calculation of warning zone length of freeway based on micro-simulation model, IEEe Access. 8 (2020) 76532–76540.
[31] D.M. Belete, M.D. Huchaiah, Grid search in hyperparameter optimization of machine learning models for prediction of HIV/AIDS test results, Int. J. Comput. Appl. 44 (2022) 875–886.
[32] Antunes, M., Litzka, J., Leben, B., La Torre, F., Weninger-Vycudil, A., Kokot, D., Mladenovic, G., Brittain, S. & Viner, H. 2008. The way forward for pavement performance indicators across Europe COST action 354 performance indicators for road pavements final report.
[33] S. Song, W. Zhang, P. Han, D. Zou, Sliding window method for vehicles moving on a long track, Vehicle Syst. Dyn. 56 (2018) 113–127.
[34] A.M. Ikotun, A.E. Ezugwu, L. Abualigah, B. Abuhaija, J. Heming, K-means clustering algorithms: a comprehensive review, variants analysis, and advances in the era of big data, Inf Sci (Ny) 622 (2023) 178–210.
[35] A.K. Jain, Data clustering: 50 years beyond K-means, Pattern. Recognit. Lett. 31 (2010) 651–666.
[36] K.P. Sinaga, M.-S. Yang, Unsupervised K-means clustering algorithm, IEEe Access. 8 (2020) 80716–80727.
[37] CENELEC, CENELEC Workshop Agreement (CWA) 18176:2025 – Decision Support System for Highway Maintenance Planning, European Committee for Electrotechnical Standardization, Brussels, 2025. January 2025.
[38] E.A. Belt, L. Yao, X. Li, N. Wang, V. Shekhar, T. Koch, E.R. Dugundji, Forecasting traffic flow by vehicle category on a major highway impacted by road maintenance works, Transp. Res. Procedia 82 (2025) 1335–1352.