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Integration of deep learning techniques and sustainability-based concepts into an urban pavement management system

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ABSTRACT

Pavement management systems (PMS) were typically developed to manage interurban networks. This paper presents an urban pavement management system (UM-PMS) that integrates all the modules of a PMS considering the particularities of the urban context. The tool uses a Geographic Information System (GIS) to import, analyze, and manage the data of the urban road network. The inspection data is obtained by an automatic equipment composed by a video camera installed on a vehicle. Images are analyzed by deep learning techniques based on Convolutional Neural Networks. Further, appropriate decisions on maintenance treatments are made by integrating multi-objective optimization and multi-criteria decision-making methods to plan efficient maintenance strategies considering economic, environmental, social, and performance objectives. Finally, the tool is applied to an urban case study to illustrate its applicability. Outcomes indicate that the proposed framework can obtain a sustainable short-term plan without losing sight of the long-term efficiency.

1. Introduction

Pavement management systems (PMS) provide the necessary framework for assessing pavement condition and selecting the adequate strategic decisions on maintenance activities to minimize the required funds and enhance road network performance (Chen & Zheng, 2021; Peraka & Biligiri, 2020). For an efficient PMS, modules for pavement inspection, condition assessment, condition prediction, optimization, and decision-making of maintenance actions must be integrated (Donev & Hoffmann, 2020). The first step is to determine pavement condition, using from manual to fully automated techniques, with the aim of minimizing subjectivity and improving efficiency (Coenen & Golroo, 2017; Ragnoli et al., 2018). Condition prediction is a necessary module for identifying the appropriate timely maintenance considering a long-term approach (Dong et al., 2015; Hassan et al., 2017). The optimization and decision-making of maintenance are crucial tasks for Highway Agencies and Operators, that is to determine the best maintenance and rehabilitation applications to preserve the road network condition under restrictive budgets (De La Garza et al., 2011). In addition, demands for a more sustainable development of the road transport system are forcing road managers to incorporate sustainability criteria in the decision-making process (Santos et al., 2019), as pavement maintenance has significant impacts on society and the environment (Chong et al., 2018).

Most of the PMS are designed for the management of interurban roads as they account for the main large corridors (Loprencipe et al., 2017). However, municipalities are increasingly demanding an effective tool to optimally allocate their budget on their road network (Zhang et al., 2013). These tools must be adapted to the urban context and overcome the lack of automatic inspection systems suitable for the urban context (Almuhanna et al., 2018; Loprencipe et al., 2017). To this regard, several considerations must be taken into account.

On the one hand, urban networks are characterized by numerous intersections, speed variability, and important traffic flow changes (Llopis-Castelló et al., 2021; Wang et al., 2013). Due to these characteristics, as well as the high cost needed to evaluate the total length of the road network, high performance equipment is not used in urban areas (Loprencipe et al., 2017; Wang et al., 2013). For instance, the International Roughness Index (IRI) is a well-known pavement index obtained by an automatic equipment, but it can only be used on roads with speed limits above 80 km/h (Loprencipe et al., 2017). Therefore,

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visual inspection is still the most common inspection method for distress identification in urban environments. Authors are claiming that manual pavement inspection is subjective, labor-intensive, and suffers from traffic disruptions (Coenen & Golroo, 2017; Gouda et al., 2021); thus, researchers are increasingly proposing Artificial Intelligent techniques to identify and quantify pavement distresses (Hadjidemetriou et al., 2018; Llopis-Castelló et al., 2021), yielding promising results to solve the inefficiencies of manual techniques. All this leads to the conclusion that there is a need to incorporate automatic techniques into the urban PMS to provide updated data of pavement condition (Peraka & Biligiri, 2020).

On the other hand, despite the differences in road operation and users between interurban and urban roads, the same optimization and decision-making modules are currently being used (Almuhanna et al., 2018). Regarding user cost, this objective largely depends on the traffic conditions and speed (Chen & Zheng, 2021; Mohamed et al., 2022), being these aspects very variable in urban areas. In addition, the evaluation of user delays during urban maintenance activities is more complex as alternative routes are different for each closed road (Chen & Zheng, 2021). Besides, PMS needs to consider the characteristics of the urban roads for a more accurate recommendation, since the urban road network plays an important role in the development of a city. At the same time, a recent review (Chen & Zheng, 2021) pointed out that little attention has been paid to the establishment of multiple indicators in multi-objective optimization (MOO) and the definition of decision-making models. This concern is shared by other researchers that claim that sustainability criteria are not commonly included into the pavement maintenance, as many studies focused on economic and performance optimization of maintenance scheduling (Denysiuk et al., 2017; Hamdi et al., 2017; Hankach et al., 2019), omitting the environmental and social dimensions of sustainability.

Therefore, it can be concluded that there is a need to develop an integrated PMS with a particular focus on urban networks. This urban PMS must solve the two main gaps highlighted above: (1) the inspection method must be improved by automatic and objective techniques that enables to assess the distresses of the pavement (Almuhanna et al., 2018; Coenen & Golroo, 2017; Loprencipe et al., 2017); and (2) the maintenance optimization system must be combined with a flexible decision-making approach that considers the sustainability aspects of the urban road network tailored to the requirements of the administration (Chen & Zheng, 2021; Loprencipe et al., 2017; Mohamed et al., 2022).

Thus, this paper presents an urban multi-objective pavement management system (UM-PMS) that fulfills these gaps through a holistic approach. This system integrates several modules based on deep learning techniques for assessing pavement condition and selecting maintenance activities under the premises of efficiency, sustainability, and objectivity. Pavement inspection is performed by an automatic equipment composed by a video camera installed on a vehicle. The images taken with this equipment are analyzed by Convolutional Neural Networks to identify, classify, and quantify the distresses in each image. Thus, this innovative inspection technique provides updated data of pavement distresses without the need for visual inspection. This information is used by the multi-objective optimization and decision-making module to provide a detailed maintenance plan according to the urban manager's needs. These modules are defined to reach the economic, environmental, social, and performance objectives of an urban road network. Therefore, this study solves the lack of urban tools to manage pavement maintenance (Almuhanna et al., 2018; Grilli & Balzi, 2023; Loprencipe et al., 2017) through an effective tool that enables urban managers to measure the road condition with the use of scarce economic resources and evaluate the most sustainable maintenance plan. This is the first tool that uses an automated technique to identify and quantify urban pavement distresses, to the best of the authors' knowledge. This step is crucial to evaluate PCI and obtain an objective indicator to compare the road network condition. In addition, this tool provides a complete planning module that considers economic, environmental, social, and performance objectives according to the urban context.

The paper is structured as follows. Section 2 analyzes the current literature on the three main aspects that this system must address: (i) techniques to detect and evaluate pavement distresses; (ii) objectives used for sustainable pavement management; and (iii) Multi-Criteria Decision-Making methodologies that can be integrated in the optimization tool to align the objectives with those of the urban managers. Based on the literature review, the methodological framework of the UM-PMS is presented in Section 3, including the input data of the tool and the results that users can visualize. Then, Section 4 is focused on the implementation of the UM-PMS for a case study in an urban district. Finally, Section 5 displays the concluding remarks, limitations, and further work.

2. Literature review

2.1. Evaluation of pavement distresses

Pavement distresses along the urban network are identified and used to estimate pavement condition in order to perform a general pavement condition analysis (Coenen & Golroo, 2017). In this regard, Pavement Condition Index (PCI) (ASTM, 2018) was defined as a standard alternative measure of the structural integrity and surface operational condition (García-Segura et al., 2022), which is calculated based on the identification and quantification of 19 types of pavement distresses. Pavement Condition Index (PCI) is adequate for urban networks as this indicator provides an overall measure of structural integrity of the pavement based on the severity and extent of the distress observed on the urban pavement (Almuhanna et al., 2018; Arhin et al., 2015; Augeri et al., 2019).

For assessing pavement distresses, the literature review points out that, in recent years, important steps have been taken on their automated detection and classification. Methods have evolved from traditional approaches, such as machine learning techniques and image processing, to modern techniques based on deep learning. Convolutional Neural Network (CNN) is a typical deep neural network that has natural advantages in computation efficiency (Hou et al., 2021). Several applications of CNN can be found in the literature during the last few years to detect distresses (Hou et al., 2021; Park et al., 2019; Zhou & Song, 2020). However, several review papers on automated inspection methods highlighted that most of the studies focus on crack classification, while few authors analyze other types of distresses (Coenen & Golroo, 2017; Peraka & Biligiri, 2020). In addition, in terms of distress quantification, most research aims at detecting and classifying distresses without calculating the severity and extension of distresses (Coenen & Golroo, 2017; Llopis-Castelló et al., 2021). In response to these gaps, a previous study introduced methodologies based on CNN for the identification, classification, and quantification of multiple urban flexible pavement distresses (Llopis-Castelló et al., 2021).

Therefore, pavement inspection must be designed according to the data required for pavement condition assessment. In the case of urban PMS, the identification and quantification of distresses is needed for performing a PCI analysis (Almuhanna et al., 2018; Arhin et al., 2015; Augeri et al., 2019). PMS require an automated and objective technique to detect the distresses of the pavement and quantify their severity and extension (Coenen & Golroo, 2017; Llopis-Castelló et al., 2021). This can be solved by obtaining images of the pavement and analyzing them by CNN (Hou et al., 2021; Park et al., 2019; Zhou & Song, 2020). This technique must be used not only for the identification and classification of the distresses, but also for their quantification (Llopis-Castelló et al., 2021).

2.2. Objectives for a sustainable pavement management

The optimization needs to integrate multiple objectives to consider the different goals of pavement maintenance management. Previous research pointed out that the economic dimension of the sustainability is always considered to achieve an efficient maintenance management (Denysiuk et al., 2017; Hankach et al., 2019). In addition, this objective must be taken into account as budget limitations are imposed by administrations (De La Garza et al., 2011). Within this dimension, agency cost and user cost can be evaluated. Agency cost considers the cost of maintenance and rehabilitation activities during the planning horizon. User cost is commonly evaluated by vehicle operation and travel delay costs (Mohamed et al., 2022). Vehicle operation cost assesses the user cost according to the pavement roughness and the average vehicle speed. Travel delay cost considers the cost increase caused by the partial/total road closure during the maintenance action. While agency cost is always considered, user cost is not always taken into account due to its difficulty in obtaining accurately and impartially results, and the tendency to dominate the decision process when considered (Golabi & Pereira, 2003; Wang et al., 2003; Wu & Flintsch, 2009).

Moreover, other objectives such as performance, environmental impact, and social impact, must also be considered to foster sustainability. The performance is usually included as one objective in multi-objective optimization, being the area between the post-treatment performance curve and the do-nothing performance curve the most used criterion (Chen et al., 2017; Khurshid et al., 2015; Mohamed et al., 2022). Regarding the environmental aspects, these are increasingly considered to find the best maintenance strategy that not only reduces the required budget, but also minimizes the environmental impact (Torres-Machi et al., 2017). Although different gas emissions can be evaluated to assess the environmental impact, a recent review pointed out that most researchers consider CO_2 emissions as the most significant (Mohamed et al., 2022). With respect to the social criteria, this dimension of sustainability is lesser extend in pavement management systems (Chen & Zheng, 2021; Mohamed et al., 2022). Furthermore, other studies have considered the impacts of construction and maintenance activities on the workers, local community, large society, and commuters (Zheng et al., 2019, 2020).

Summarizing, the objectives presented can be considered to develop more efficient systems that optimally achieve the sustainability objectives. Some of these objectives have been used for urban applications, like road condition, economic cost, and greenhouse gas emissions (Chong et al., 2018; Saha & Ksaibati, 2018; Sun et al., 2020; Torres-Machi et al., 2018). However, to achieve an urban UM-PMS that undertakes the strategic goals of the sustainability development, the multi-objective optimization need to simultaneously consider the cost, performance, environment, and social objectives (Chen & Zheng, 2021; Mohamed et al., 2022). In addition, further work is needed to adapt the objectives to the characteristics of the urban networks (Llopis-Castelló et al., 2021; Wang et al., 2013).

2.3. *Multi-Criteria Decision-Making: Integrated value model for sustainable Assessments*

Multi-criteria decision-making methods (MCDM) have been widely used over the past few years to help project managers in the selection processes related to the construction (Jato-Espino et al., 2014). Some authors point out that the integration of the multi-objective and the MCDM methodologies is the need-of-the-hour to provide tailor-made solutions to the global pavement maintenance crisis (Chen & Zheng, 2021). The decision-making techniques can be used not only to compare or rank a set of alternatives, but also to incorporate the decision-maker preferences into the searching for the more optimal maintenance plan.

Among these techniques, the Integrated Value Model for Sustainable Assessments (MIVES) has demonstrated its potential when managing sustainable problems in complex scenarios (Aguado et al., 2012; Jato-Espino et al., 2014). MIVES is part of the group of the utility and value methods, which are used to convert the quantitative and qualitative assessment of criteria into a degree of satisfaction (Penadés-Plà et al., 2016). This method was designed to incorporate value function and satisfaction concepts in the MCDM process (Pons & De La Fuente, 2013), especially for the sustainability evaluation (Jato-Espino et al., 2014; Pujadas et al., 2019). Therefore, this method can be used to provide the decision-maker preferences regarding quantitative and qualitative sustainability criteria.

MIVES is characterized by following these three steps: (1) designing a hierarchical scheme for determining the relative importance among the elements of each level; (2) selecting the shape of the value functions for transforming the value of each objective into a normalized value between 0 and 1 according to the satisfaction grade; and (3) assessing the alternatives by aggregating the results of each objective multiplied by the weights for each level. The first step is particularly suitable for dealing with sustainability problems, as the evaluation of the most sustainable alternative is done by aggregating the economic, environmental, social, and technical criteria. The second step focuses on the intra-criterion evaluation which uses value functions to provide a normalized value from the evaluation of the objectives. In this regard, value functions can be increasing functions (Equation (1) and (3) or decreasing functions (Equation (2) and (3). These functions are defined assigning a numerical value to the parameters, which determine how each value of the objective corresponds to the dimensionless scale (Pons & De La Fuente, 2013).

$$V_{ob,i} = B_i \cdot \left[1 - e^{-k_i \left(\frac{|X - X_{\min}|}{C_i} \right)^{P_i}} \right] \tag{1}$$

$$V_{ob,i} = B_i \cdot \left[1 - e^{-k_i \left(\frac{|X_{\max} - X_i|}{C_i} \right)^{P_i}} \right] \tag{2}$$

$$B_i = \left[1 - e^{-k_i \left(\frac{|X_{\max} - X_{\min}|}{C_i} \right)^{P_i}} \right]^{-1} \tag{3}$$

where X is the value of the indicator, X_{min} is the minimum value adoptable by the objective; X_{max} is the maximum value adoptable by the objective; P_i is a factor that determines the shape of the function; and C_i and K_i are respectively the values of the abscissa and the ordinate in the inflection point of the function.

In case of the objectives are preferably normalized without shaping the value of the indicator, a linear relationship can be calculated for increasing (Equation (4) and decreasing (Equation (5) functions.

$$V_{ob,i} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{4}$$

$$V_{ob,i} = \frac{X_{\max - X_i}}{X_{\max} - X_{\min}} \tag{5}$$

Finally, the third step defines the inter-criteria evaluation to obtain the global evaluation. The global evaluation of an alternative (V_i) is obtained adding the value of the objectives ($V_{ob,i}$) multiplied by the corresponding weights ($W_{ob,i}$), as Equation (6) expresses.

$$V_i = \sum_{i=1}^{n} W_{ob,i} \cdot V_{ob,i} \tag{6}$$

Based on the above, MIVES technique can be integrated in the multi-objective optimization to incorporate the decision-maker preferences into the searching for the optimum timely maintenance. This would provide a flexible decision-making tool that would solve the need of tailor-made solutions (Chen & Zheng, 2021). For that, the value functions and the weights must be defined according to the requirements of the administration.

3. Urban Multi-objective pavement management system

The UM-PMS was designed to integrate the basic components of a PMS into a flexible and easy tool to be used by urban managers for controlling the pavement condition and providing the optimal maintenance plan according to their needs. The components of the UM-PMS were defined after analyzing the literature review and pointing out the current weaknesses that must be solved. The tool follows a framework based on the steps needed from the creation of the urban road network map to the delivery of the planning results. This framework is summarized in Fig. 1. The first step focuses on the development of the urban map, integrating the road network information and traffic data for subsequent analyses. The tool uses a Geographic Information System (GIS) to analyze and display the geographically referenced information. Then, an automatic inspection is developed through a videorecording of the pavement which is decomposed into images. These images are analyzed by two CNN. The first CNN identifies all urban pavement distresses that are present in each image. The second CNN aims at quantifying the identified distresses. The geographical information of each image and the results of the CNNs are used to estimate the severity and extension of distresses. Based on this, the PCI of each segment is evaluated. Next, the condition is predicted over the planning horizon according to the urban characteristics. A multivariable regression model for flexible urban pavements considering the combined influence of climate and traffic conditions is incorporated into the tool. Finally, a holistic approach combines the MCDM and multi-objective methodologies. The decision-making parameters are firstly defined into the MCDM framework. MIVES technique is used to provide the decision-maker preferences and obtain a global objective evaluation. Then, the multi-objective optimization uses Simulated Annealing algorithm to obtain an optimum and sustainable maintenance plan that defines the maintenance schedule during the planning horizon. Table 1 summarizes the methods of all the UM-PMS modules, as well as their advantages and disadvantages. The following sub-sections explain in detail these methods.

According to the conclusions of the literature review, there is a need to consider sustainability objectives that represent the urban needs and define the MCDM parameters to provide the decision-maker preferences. Following this, an expert panel in pavement management was invited to participate in a focus group. The focus group technique was selected to integrate the opinions of experts (Montalbán-Domingo et al., 2021), as this method promotes the discussion of different stakeholders to generate a consistent and holistic viewpoint (Yu et al., 2017) and the creation of new data based on the expertise of the participants (Xenarios & Tziritis, 2007).

To carry out the focus group, it is important to define a representative group according to their expertise (Bhandari & Hallowell, 2021). Accordingly, four types of stakeholders were defined to cover all the agents involved in the urban pavement maintenance management: Stakeholder 1 - engineers of the urban maintenance division of a construction company; Stakeholder 2 - engineers of the urban maintenance division of a consulting company; Stakeholder 3 - local road managers of public-sector; and Stakeholder 4 - researchers with doctoral degree and more than three peer-reviewed journal articles in road maintenance field. Two experts of each profile were invited to the focus group, considering that all experts must have at least 10 years of professional experience and a BSc degree (Montalbán-Domingo et al., 2021). The following sub-sections describe the tool framework, the input data, and the results displayed by the user interface.

3.1. Road network creation and data integration

The first step aims to develop the road network with the information needed for the following modules (characteristics of roads and traffic). The UM-PMS tool uses GIS to import, analyze, and manage the data of the urban road network. GIS displays the geographically referenced information creating a map from the location data (Almuhanna et al., 2018; Debnath, 2022). Specifically, the urban road network is represented by a graph. The user of the tool must obtain the graph from OpenStreetMap; this digital map database contains the data needed to

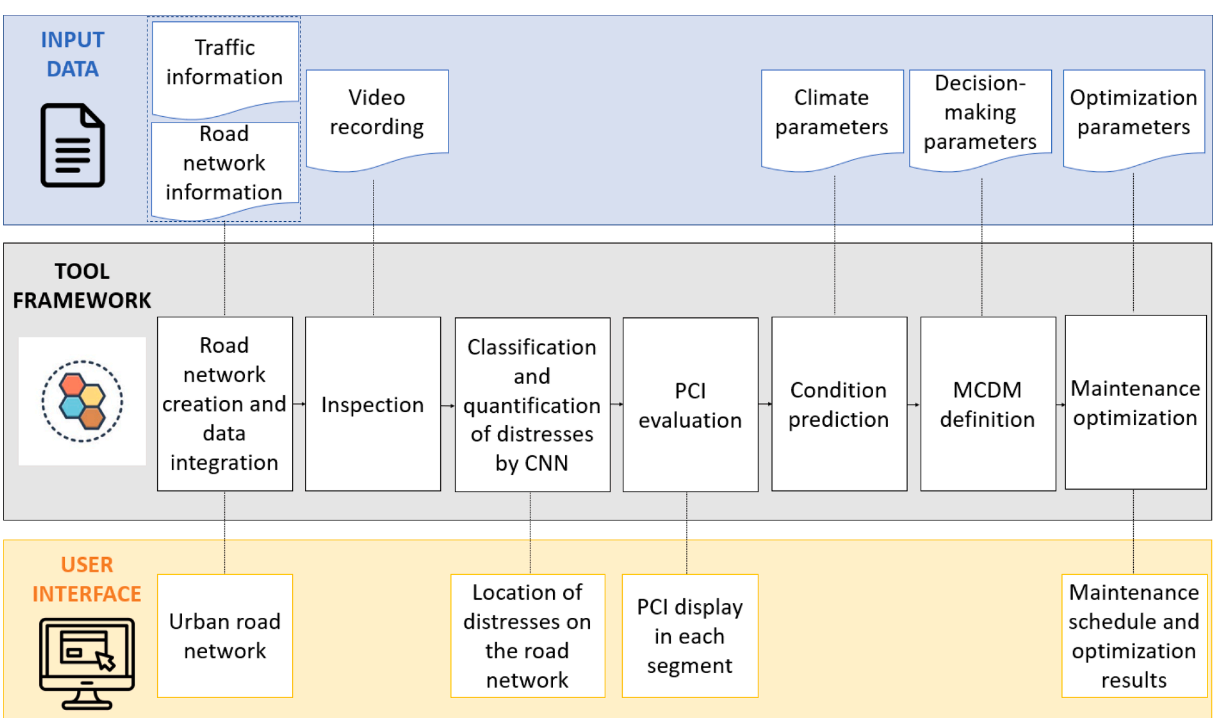


Fig. 1. Urban pavement management system: tool framework, input data, and user interface.

Table 1
Methods used for the UM-PMS: advantages and disadvantages.

Module	Method	Advantages (A) and Disadvantages (D)	References
Road network creation and data integration	GIS	A: Enable to manage, analyze and display geographically referenced information D: Information must have a compatible file type	(Almuhanna et al., 2018; Debnath, 2022)
Inspection	Videocamara	A: Lower price, easy to install, short inspection time D: Lower resolution than professional sensors and high dependency on lighting conditions	(Coenen & Golroo, 2017; Mei & Gül, 2020; Peraka & Biligiri, 2020)
Classification and quantification of distresses	Convolutional Neural Network (CNN)	A: CNN has natural advantages in computation efficiency and accuracy D: CNN cannot evaluate distresses under different conditions than those of data training	(Hou et al., 2021; Park et al., 2019; Zhou & Song, 2020)
Pavement condition assessment	PCI	A: Provide a standard alternative measure of the structural integrity and surface operational condition D: The severity and extension of distresses must be evaluated	(Almuhanna et al., 2018; Arhin et al., 2015; Augeri et al., 2019)
Condition prediction	Multivariable regression model	A: Considers the combined influence of the most influential factors related to climate and traffic conditions D: The model is limited to particular cases (flexible pavements in urban areas). Data of climate and traffic must be provided	(Llopis-Castelló et al., 2020; Osorio et al., 2014).
MCDM definition	Integrated Value Model for Sustainable Assessments (MIVES)	A: Manage sustainable problems in complex scenarios. Convert the quantitative and qualitative assessment of criteria into a degree of satisfaction Incorporate the decision-maker preferences prior to the optimization D: Calibrate value functions and weights	(Aguado et al., 2012; Jato-Espino et al., 2014; Pons & De La Fuente, 2013; Pujadas et al., 2019).
Maintenance optimization	Simulated Annealing	A: This algorithm avoids getting trapped in local optimum enabling the process to reach the global optimum D: It requires the calibration of the initial temperature, the Markov Chain, the cooling rate, the reheat threshold and the stop criterion	(Goh et al., 2017, 2019; Martínez-Muñoz et al., 2021; Paya-Zaforteza et al., 2010).

create the urban map. In addition, the file format is compatible with GIS. The nodes of the graphs are generated at the intersection between urban roads. Thus, the road segments are defined as the elements between two nodes. Each segment contains attributes, such as the name of the street and the type of road (primary road, secondary road or highway). These attributes can be obtained directly from OpenStreetMap. The UM-PMS tool also provides the option of dividing the segments longer than a maximum value proposed by the user.

In addition to the road network map, the traffic information must be imported to the model. In this case, the Annual Average Daily Traffic (AADT) and Annual Average Daily Truck Traffic (AADTT) are downloaded from local administrations and imported to the UM-PMS using GIS. Besides, the tool allows the modification of the attributes of the segments. The user can download a csv file with the data of the segments and modify its content. Then, this csv can be uploaded to the UM-PMS to update the data.

Therefore, this step provides the parameters related to the characteristics of roads and traffic that will be relevant inputs for the following steps. The user interface shows the urban road network and its information in layers. A layer controller is available on the right side to activate or deactivate the different layers.

3.2. Inspection

The inspection focuses on obtaining the images that will be analyzed to detect the pavement distresses. This is carried out by a Garmin Virb Ultra 30 video camera, which is mounted on the rear of a vehicle by a gripper suction system suitable for installation on any vehicle (Fig. 2). This inspection technique is low cost, easy to install, and requires short inspection time (Coenen & Golroo, 2017; Mei & Gül, 2020; Peraka & Biligiri, 2020). A video is recorded from a zenithal position at 1.4 m high. The vehicle must be traveling at 50 km/h maximum speed, which is consistent with the maximum speed allowed within city limits. However, this technique provides lower resolution than professional sensors and has high dependency on lighting conditions. Therefore, the analysis method must be designed to overcome these limitations.

Fig. 2. Pavement inspection equipment.

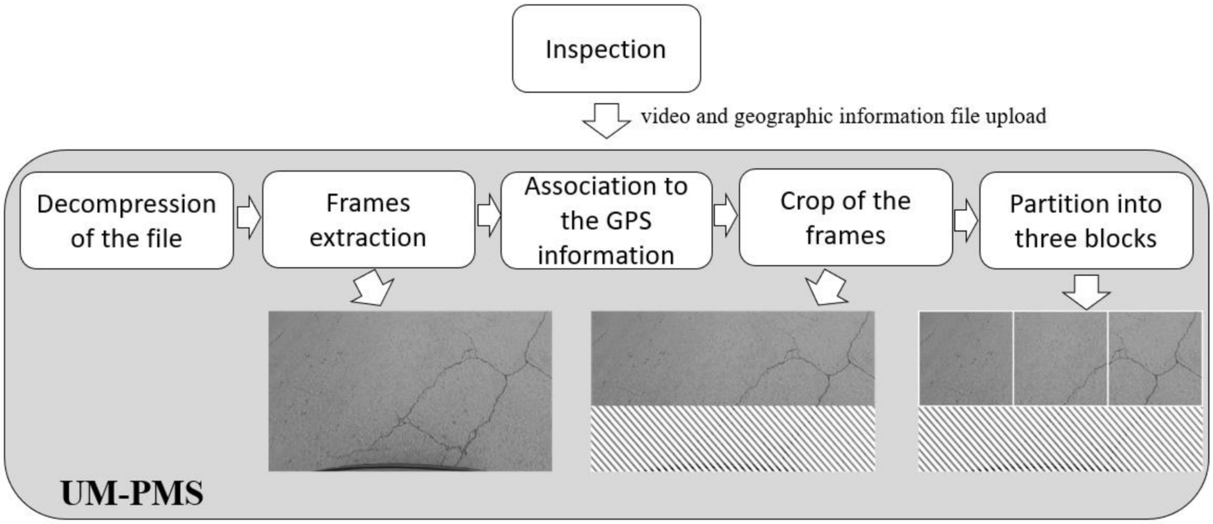


Fig. 3. Flowchart of inspection and UM-PMS process to obtain the blocks from each frame.

When the inspection is finished, a compressed file is uploaded to the UM-PMS containing the video and the geographic information file. The tool carries out an internal process consisting in five stages (Fig. 3): (1) decompression of the file, (2) video processing and frames extraction, (3) association of each frame to the GPS information, (4) crop of the frames to remove the part of the vehicle captured in the frame, and (5) partition of the frames into three blocks of 256 × 256 pixels. This last step is implemented to minimize the number of distresses in each block and improve the accuracy of the automatic technique for distresses identification and quantification. To sum up, the inspection module only requires that users record the video and upload the file. Then, the tool automatically performs the internal process and returns the frames for the following step.

3.3. Classification and quantification of distresses by CNN

The objective of this step is to calculate the distresses of each segment of the road network for later assessing PCI. To this end, blocks obtained in the previous module are analyzed using Deep Learning techniques to identify, classify, and quantify the multiple urban flexible pavement distresses. The methodology proposed (Llopis-Castelló et al., 2021) uses two types of Convolutional Neural Networks to characterize and quantify the damages detected in the images. This technique is more efficient and can obtain more accurate results than those achieved by methods based on other machine learning techniques (Hou et al., 2021; Park et al., 2019; Zhou & Song, 2020). This method can extract the morphological characteristics of the distresses through increasing levels of feature abstraction. Thus, this method can detect distresses under different situations such as uneven lighting condition, as long as the training data include all these situations (Zhou & Song, 2020).

The first CNN (CNN_1) allows for the identification of the most common types of distress in urban road networks: longitudinal cracking, transverse cracking, alligator cracking, raveling, potholes, and patching. CNN_1 takes each image to detect every type of distress, reporting a multilabel of these six distresses, also including road markings and sewer traps. Then, a second CNN (CNN_2) is implemented to quantify the distresses via image segmentation. Thus, CNN_2 uses only those images with distresses detected by the first CNN to measure the severity and geometric dimensions of the distresses needed to assess the PCI, i.e., length, width, and area. In this regard, four CNN_2 are used to evaluate the following distresses: (1) longitudinal cracking, (2) transverse cracking, (3) potholes, and (4) patching. In the case of alligator cracking and raveling, the whole image was considered as damaged because these types of distress usually took up a large area of the image (greater than80%). CNN_2 of longitudinal and transverse cracking assesses the length and width of the crack. Regarding potholes and patching, CNN_2 provides the area of the distresses. To perform this module, it is important that frames were then resized to 256 × 256 pixels to meet the requirements of ImageNet configuration, which is an image database commonly used for object recognition research.

CNN_1 was designed on a ResNet architecture. Particularly, this model uses the ResNet34 architecture. Regarding CNN_2, the architecture used for image segmentation is the U-Net. CNNs were trained to obtain accurate results of precision, recall, F1 score, and intersection over union (IoU). Results of CNN_1 were: 0.9317 precision, 0.9252 recall, and 0.9262 F1 score. Regarding CNN_2, the global IoU was 0.6821 for longitudinal cracks, 0.6709 for transverse cracks, 0.8760 for patches, and 0.6870 for potholes. The hole detail and justification of the CNNs can be found in Llopis-Castelló et al. (2021).

Therefore, this step takes the frames of previous module and performs these CNNs. Firstly, the frames are displayed on the road network map as each image is georeferenced. Then, the distresses and their quantification are associated with each frame. Thus, after implementing this module, users can see the frames and distresses of each segment on the road network.

3.4. Pavement condition evaluation

Pavement condition is estimated by the Pavement Condition Index (PCI). This index uses the information of the severity and extent of the distresses to provide an overall measure of the structural integrity of a segment. A value between 0 and 100 is obtained, being 100 the best pavement condition. The method for the calculation of PCI can be found in ASTM (2018). This model uses two relevant parameters: extension and severity of each distress. Therefore, this step calculates PCI based on the results of the identification and quantification of the distresses. This module aggregates all the distresses of a segment according to their severity to obtain the PCI of each segment. This output can be visualized in a layer of the GIS tool. PCI of each segment is displayed based on the PCI standard scale (ASTM, 2018). Therefore, the CNN results provide the data needed to evaluate the PCI of the road network. This solves the problem of traditional methods by reducing subjectivity, workload and traffic disruptions.

3.5. Condition prediction

This module evaluates the evolution of PCI according to the characteristics of the road. Pavement condition prediction models are needed to know the future condition of the urban road network. This step is essential for the effective long-term budget planning and the coordination of maintenance actions in the network (Dong et al., 2015; Hassan et al., 2017). Without timely intervention, there is a high probability that maintenance treatments will be more expensive, incurring in additional risks (AASHTO, 2011). Most of the existing models have been calibrated to be used in interurban roads, so their application to urban environment can be unrepresentative because of the important differences in traffic demand, network characteristics, and pavement design (Llopis-Castelló et al., 2020; Osorio et al., 2014).

Thus, this research used the prediction model proposed by Llopis-Castelló et al. (2020) which was defined for flexible urban pavements considering the combined influence of the most influential factors related to climate and traffic conditions based on the historic urban pavement data provided by the Long-Term Pavement Performance (LTPP) program. More specifically, the deterioration model depends on the age of the pavement (p_a), calculated as the difference between the date of the current pavement assessment and the date of the pavement construction, the Equivalent Single Axle Load in thousands (*KESAL*), and the annual average temperature (*AAT*) (Equation (7).

$$PCI = 137.43 - 6.60 \bullet p_a - 0.0196 \bullet KESAL - 3.89 \bullet AAT + 0.1847 \bullet AAT^2 \tag{7}$$

while *KESAL* and *AAT* must be provided as input data, p_a is assessed adding the years of the prediction to the age of the pavement.

Therefore, to execute this module, users must provide the annual average temperature. Traffic information is taken from the GIS information. In this way, the evolution of PCI of each segment is provided as output. Note that this method is limited to flexible pavements in urban areas.

3.6. MCDM definition

UM-PMS combines the MCDM and multi-objective methodologies to consider the decision-maker preferences into the searching for the more optimal maintenance plan. Firstly, the MCDM module is used to define the urban manager parameters through the value function and satisfaction concepts of MIVES. This method provides a global evaluation of an alternative, which is used in the objective assessment of the optimization. Therefore, the objective of this module is to provide the decision-makers preferences. In this regard, they take part in the initial stage introducing their preference to later obtain an optimum and sustainable maintenance plan according to their requirements.

To define this module, the authors firstly analyzed the objectives published in the literature. Then, the expert panel selected and defined the objectives to address the urban requirements. The literature review pointed out that multiple objectives —economic, environmental, social, and performance objectives— must be used to address the overall aims of an urban network from a sustainable point of view. This way, the expert panel decided to include the cost of maintenance actions during the planning horizon (economic criterion), the CO_2 emissions of maintenance actions during the planning horizon (environmental criterion), and the improvement of network condition as the area between the post-treatment performance curve and the do-nothing performance curve (performance criterion). However, the expert panel concluded that the user cost should not be considered using the equations proposed in the literature, as both vehicle operation and travel delay costs are calculated based on the traffic conditions, speed, and alternative routes, and these parameters are highly variable in urban areas (Chen & Zheng, 2021; Choi, 2019). Instead, they considered that the social impact of the inconvenience caused by maintenance actions to user should be considered using an intra-criterion evaluation. In addition, they concluded that social aspects such as the type of road (primary, secondary, etc.), the district or the neighborhood where the road segment is located can affect significantly on the decision about the maintenance strategy. Therefore, they included two objectives, which were called "impact on users" and "contribution to the social development", to the three selected from the literature review. In conclusion, five objectives were proposed: (O1) cost, (O2) CO_2 emissions, (O3) impact on users, (O4) contribution to the social development, and (O5) improvement of network condition.

Based on MIVES methodology, the objectives are combined into a global evaluation using weights. In addition, value functions are used for transforming the value of each objective into a normalized value between 0 and 1 according to the satisfaction grade. Fig. 4 shows the user interface to provide the parameters needed. The relevant parameters are: the weights; the unit costs and emissions; and the parameters of value functions. These parameters are used to obtain the global evaluation of each maintenance strategy. This model is integrated into the following module —multi-objective optimization— for assessing each maintenance alternative during the optimization process. The methodology to assess each objective and the parameters needed as input data are detailed below.

3.6.1. O1: Cost

The cost of each maintenance action is assessed according to the condition of the pavement and the distresses observed at the inspection. To define the most common treatments used in urban road networks, the expert panel decided to, firstly, differentiate local repairs from complete repairs. Local repairs are carried out on segments that only exhibit potholes or longitudinal and transverse cracking. As local repairs are applied on the damaged area, the cost is measured by aggregating the cost of each treatment multiplied by the area of each distress. When there are other types of distresses, a PCI evaluation is recommended distinguishing between surface treatment, surface and base treatment, and full-depth replacement. In addition, distresses can only be accurately determined the year of the inspection ($t = 0$). Therefore, for subsequent years of the planning horizon, the treatment is also selected according to the PCI obtained from the prediction model. The ranges of the PCI for each treatment are proposed by the expert panel. The cost is calculated multiplying the unit cost of the treatments by the total area of the segment. In addition, a discount rate of 4% is considered (Deshpande et al., 2010; Yao et al., 2020). In this regard, the cost is calculated as follows (Equation (8):

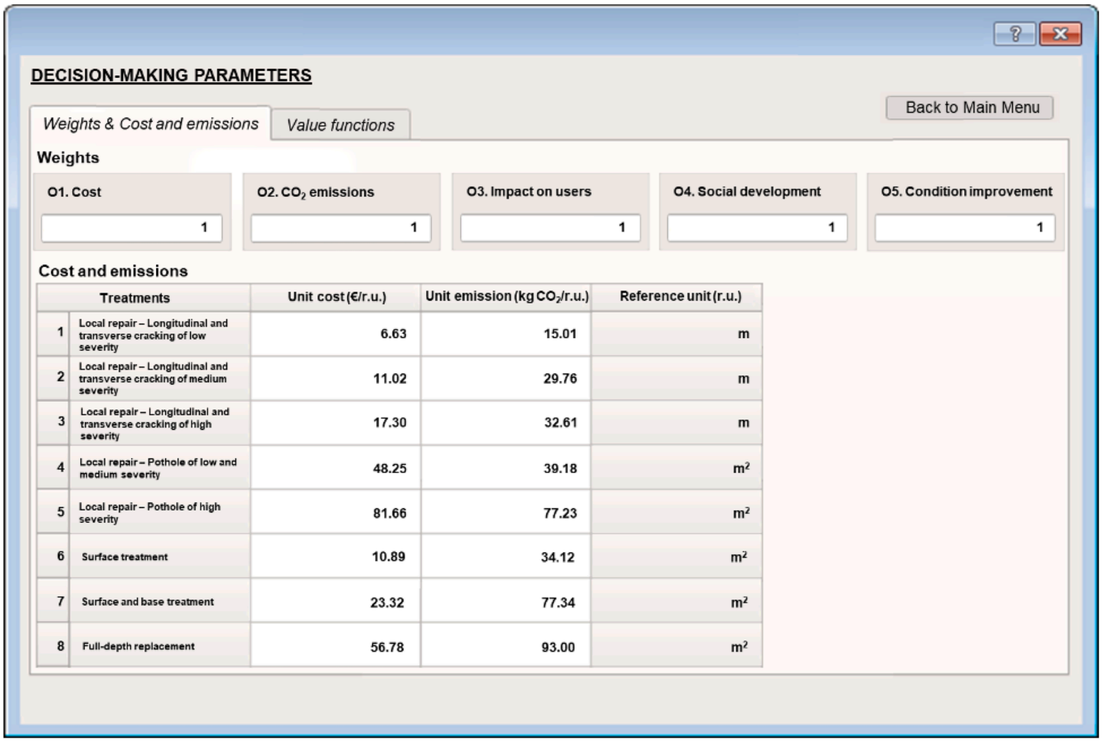
$$C = \sum_{j=1}^{T} \frac{\sum_{i=1}^{N} C_{ij} * A_i}{(1+v)^j} \tag{8}$$

where C is the total cost, C_{ij} is the unit cost of the treatment applied to the segment i at year j, A_i is the area or length repaired that should be considered according to the reference unit (Fig. 4), ν is the discount rate, N is the total number of segments that are repaired at year j, and T is the planning horizon. Unit costs were obtained from a Spanish database (ITEC, 2020). They were evaluated as the sum of the cost of material production, transport, and placement.

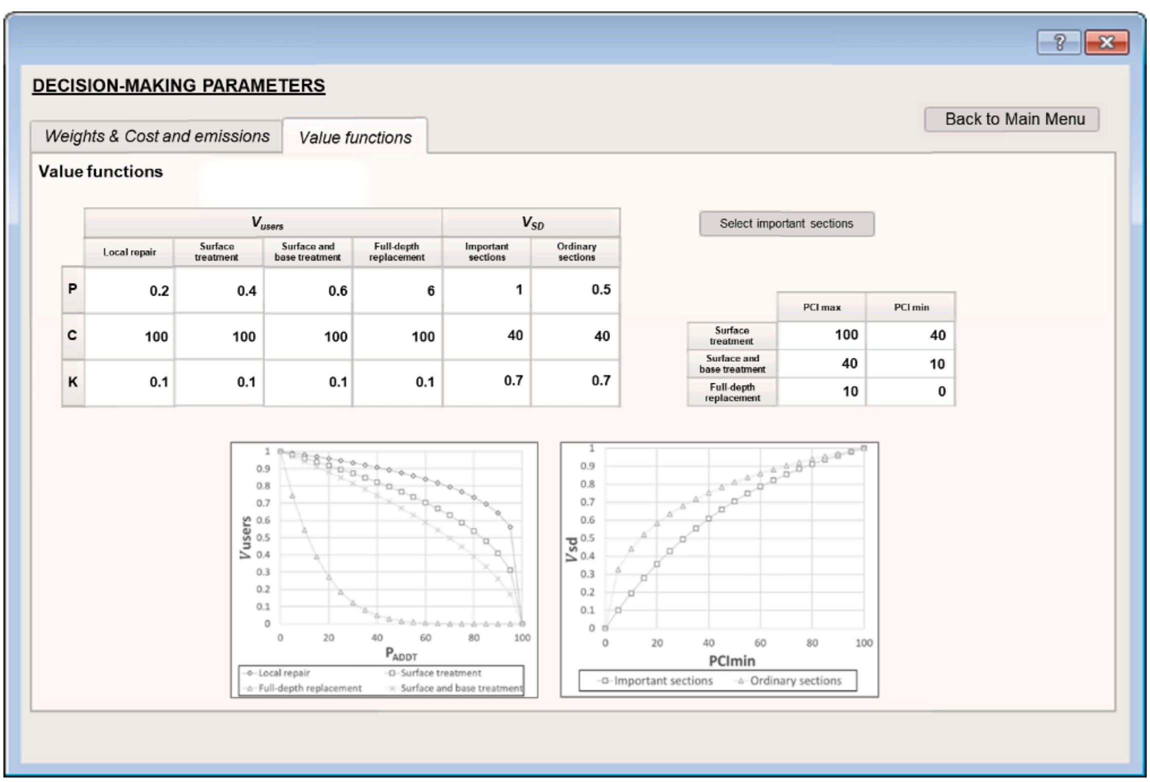
Once the cost during the planning horizon is calculated, a linear relation is used to normalize the value of this objective (Equation (5), being X equal to the cost. The parameters needed to evaluate this objective are shown in Fig. 4. The expert panel provided some reference values for all of them, so the user can use or change them.

3.6.2. O2: CO_2 emissions

This objective assesses the kilograms of CO_2 emissions associated with the maintenance actions. The procedure used to evaluate this objective is the same as that of the economic cost, considering the unit emissions instead of the unit cost. A linear relationship (Equation (5) is also used to obtain the value of the objective, being equal to CO_2



(a)



(b)

Fig. 4. Decision-making parameters: (a) weights, cost, and emissions; (b) value functions.

emissions. The reference values provided for the MCDM parameters (Fig. 4) were obtained from a national database (ITEC, 2020) considering the environmental impact of the extraction of raw material, transformation of materials needed for the treatment, transport, and all the construction activities including the equipment needed for the maintenance application.

3.6.3. O3: Impact on users

This objective evaluates the impact on users due to the closure of the road or the reduction of the speed during the maintenance activity. This objective is evaluated using the value functions (Equation (1) and (3) according to the main parameters influencing the valuation. The expert panel selected two main parameters: the type of treatment and the average annual daily traffic (AADT). The type of treatment influences the duration and the magnitude of the inconvenience that these treatments cause to users. The AADT gives information about the number of users affected. According to this, the value functions are defined using the percentile of the AADT (P_{AADT}) as an input variable. The type of treatment (local repair, surface treatment, surface and base treatment, and full-depth replacement) determine the shape of the value function. Therefore, the value of impact on users (V_{users}) is calculated by Equation (1) and (3) considering that X is the percentile of the AADT, X_{min} is 0, X_{max} is 100, and P_i, C_i, and K_i are defined for each type of treatment. The values of the parameters that must be introduced are also suggested by the expert panel (Fig. 4). These were obtained considering that, for $P_{AADT} = 50$, V_{users} will be proportional to the duration of the maintenance treatment. The graphic representation of the value functions is also provided in Fig. 4 for a better understanding.

3.6.4. O4: Contribution to the social development

The goal of the fourth objective is to maximize the road contribution to the social development. One of the main objectives of an urban network is to connect strategic social points in a city and provide good services to road users. Hence, it is important to keep roads in good condition to guarantee their social function, especially in those segments that have a higher level of importance because they are vital for the social development of the city. To achieve this goal, two parameters were proposed: the minimum PCI (PCI_{min}) of the segment during the planning horizon and the importance of the segment. The PCI_{min} is calculated as the minimum value of PCI during the planning horizon.

Regarding the importance of the segment, two levels were established by the expert panel: important segments and ordinary segments. The important segments are either those that are near a strategic point of the city or they have a principal role in the user mobility. The value of contribution to the social development (V_{sd}) is calculated by Equation (2) and (3) considering that: X is PCI_{min}, X_{min} is 0, X_{max} is 100, and P_i, C_i, and K_i are defined according to the importance of the road. The values of the parameters are suggested (Fig. 4) considering that the increment in V_{sd} must be higher in important segments to encourage their improvement. Two procedures are provided to the decision-maker to select the importance of the roads: (1) selecting strategic points of the city and its radius of action to capture the segments which are prioritized, and (2) determining the strategic segments due to their primary role. Therefore, important segments are those that accomplish any of these requirements, while ordinary segments are those that do not fulfill any of them.

3.6.5. O5: Improvement of network condition

This objective measures the area between the post-treatment performance curve and the do-nothing performance curve using Equation (9) (Chen et al., 2017; Khurshid et al., 2015; Mohamed et al., 2022).

$$ob_5 = A_{PT} - A_0 = \int_{t=0}^{t=T} PCI_{PT,t} - \int_{t=0}^{t=T} PCI_{0,t} \tag{9}$$

where A_{PT} is the difference between the area bounded by the post-treatment performance curve, A_0 is the area bounded by the do-nothing performance curve, $PCI_{PT,t}$ is the PCI of the post-treatment performance curve at t year, $PCI_{o,t}$ is the PCI of the do-nothing performance curve at t year, and T are the years of the planning horizon. Finally, a linear relationship for the value function is considered using Equation (4), being X equal to ob_5.

3.7. Maintenance optimization

The objective of this module is to determine the best maintenance plan; that is, the most sustainable treatment that must be applied to each segment during each year of the planning horizon. For this purpose, the maintenance optimization aims at maximizing the objective function F (Equation (10) while satisfying the constraints G_j (Equation (11). The objective function is the global evaluation obtained through the MCDM module. The constrains check whether the maintenance plan fulfils the minimum performance and budget conditions. This module also calls the condition prediction module to estimate the PCI evolution through the planning horizon. The objective functions and constraints depend on the variables x_n and the parameters p_m. The heuristic optimization algorithm searches for candidate solutions, varying the value of the variables, toward finding optimal or near-optimal solutions. These variables define the optimal maintenance plan. The parameters are those fixed values of the road network determined by the case study. The maintenance optimization takes the parameters from the GIS information. Therefore, this module needs the support of the other modules to determine the objective function, the constraints, and the parameters.

$$F(x_1, x_2, \cdots, x_n; p_1, p_2, \cdots, p_m) \tag{10}$$

$$G_j(x_1, x_2, \cdots, x_n; p_1, p_2, \cdots, p_m) \leq 0 \tag{11}$$

The definition of variables is an essential step in the optimization model. The number of variables and their number of the possible values condition the size of the combinatorial problem. Usually, in pavement management, the decision variables define which treatment must be applied to each segment during each year of the planning horizon, entailing a complex combinatorial problem (Torres-Machi et al., 2017; Zhang et al., 2013). However, this study proposes a change of focus based on condition-based maintenance (Alrabghi & Tiwari, 2015). Thus, the variables define the maintenance thresholds that triggers maintenance actions to restore the pavement condition to the initial condition (PCI = 100). With this proposal, only one variable is needed for each segment with the consequent reduction in the computing time. Therefore, users must define the possible maintenance thresholds or strategies (hereinafter "strategy (S)"), so the algorithm will find the optimum one. The expert panel proposed three possible strategies for the variables: S70, S40, and S10. In this regard, maintenance treatment occurs at the end of each treatment range, guaranteeing that resources would not be wasted inefficiently.

On the other hand, constraints limit the value of some indicators, reducing the solution space of feasible solutions. In maintenance planning, constraints commonly control the performance of the road network and budget (Chen & Zheng, 2021). Regarding the performance, most research studies impose the minimum condition level as a constraint. However, the approach proposed for defining the variables, determines the possible strategies of a segment. Therefore, this approach enables to eliminate the performance constraint, as the minimum condition level would be the most restrictive strategy. For example, if the decision-maker defines three possible strategies for the variables (S70, S40, and S10), the performance threshold would be 10, as there cannot be a segment with a lower condition than 10.

Concerning the budget constraint, a penalization technique is proposed. Penalties are implemented for the infeasible solutions, worsening the aptitude of these solutions according to a penalty function (Alrabghi & Tiwari, 2015; Van Horenbeek & Pintelon, 2013). A penalty is proposed for limiting the budget (Equation (12).

$$P_g = 1 + \frac{\Delta C}{C_{max}} \tag{12}$$

where P_g is the penalty, C_{max} is the maximum budget assigned by the user, ΔC is the difference between the cost of the analysis period and the maximum budget.

The heuristic algorithm used in this research is simulated annealing (SA). SA bases its search strategy on the analogy of crystal formation. This algorithm avoids getting trapped in local optimum thanks to its ability to accept solutions that initially worsen the outcome but ultimately enable the process to reach the global optimum (García-Segura et al., 2014; Goh et al., 2017). It has been proved that this algorithm can converge to its global optimality if enough randomness is used in combination with very slow cooling (Yang, 2014). These characteristics make the algorithm appropriate to optimize engineering problems that require to solve combinatorial problems (Goh et al., 2017, 2019; Martínez-Muñoz et al., 2021; Paya-Zaforteza et al., 2010). This process is governed by the Boltzmann distribution $\exp(-\Delta E/T)$, where ΔE is the change of energy, equivalent to variation of the objective function when evaluating a new configuration and T is the temperature. The initial temperature (T_{ini}) is adjusted according to the method proposed by Medina (2001), which increases or decreases the initial temperature until the percentage of acceptances is between 20 and 40%. The temperature is reduced once a Markov Chain ends according to the expression $T_{i+1} = kT_i$, where k is the cooling rate. Thus, the probability of accepting worse solutions drops with each Markov Chain (L_{MC}) to reach the optimum solution. After each Markov chain, the algorithm checks whether the search is stuck in a local optimum, that is to say, the best solution is the same and the percentage of solutions accepted is less than a threshold T_r. In this case, the temperature is reheated according to *F(current solution)·A*, where A is obtained after the calibration of the initial temperature. A is calculated as T_{ini}/*F(initial solution)*, where T_{ini} is the initial temperature and *F(initial solution)* is the value of the objective function of the initial solution. The algorithm ends when the number of Markov Chains without improvement reaches a value N_{max}. The calibration of the algorithm SA indicated that the best performance was obtained for $L_{MC} = 1000$, $k = 0.8$, $T_r = 0.1$, and $N_{max} = 10$.

Therefore, the optimization parameters that users must introduce as input data are: (i) the possible strategies for the variables, (ii) the years of the planning horizon, and (iii) the maximum budget. These parameters are relevant to obtain the optimal maintenance plan that fits the infrastructure manager's needs. This module takes these parameters and uses the information of the condition prediction and MCDM modules to find the optimal maintenance plan. Results of the maintenance schedule, the objective functions, and the strategy of each segment are provided by UM-PMS.

4. Case study

The UM-PMS was implemented in an urban district of Valencia (Spain): L'Eixample. This district is characterized by its commercial area and historic buildings. In addition, it hosts the main transportation systems: multiple bus routes, the main railway station of the city, and

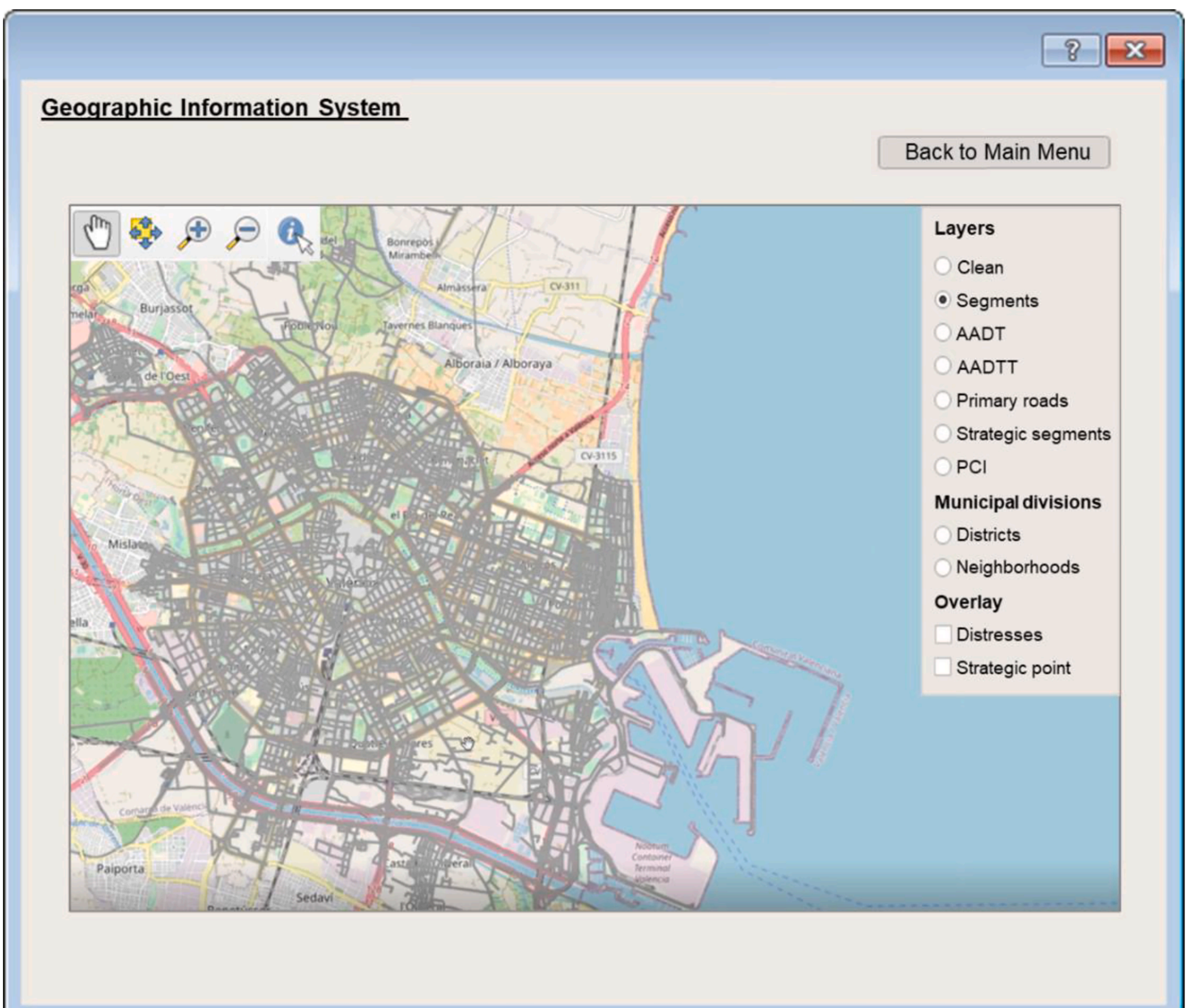


Fig. 5. Valencia road network.

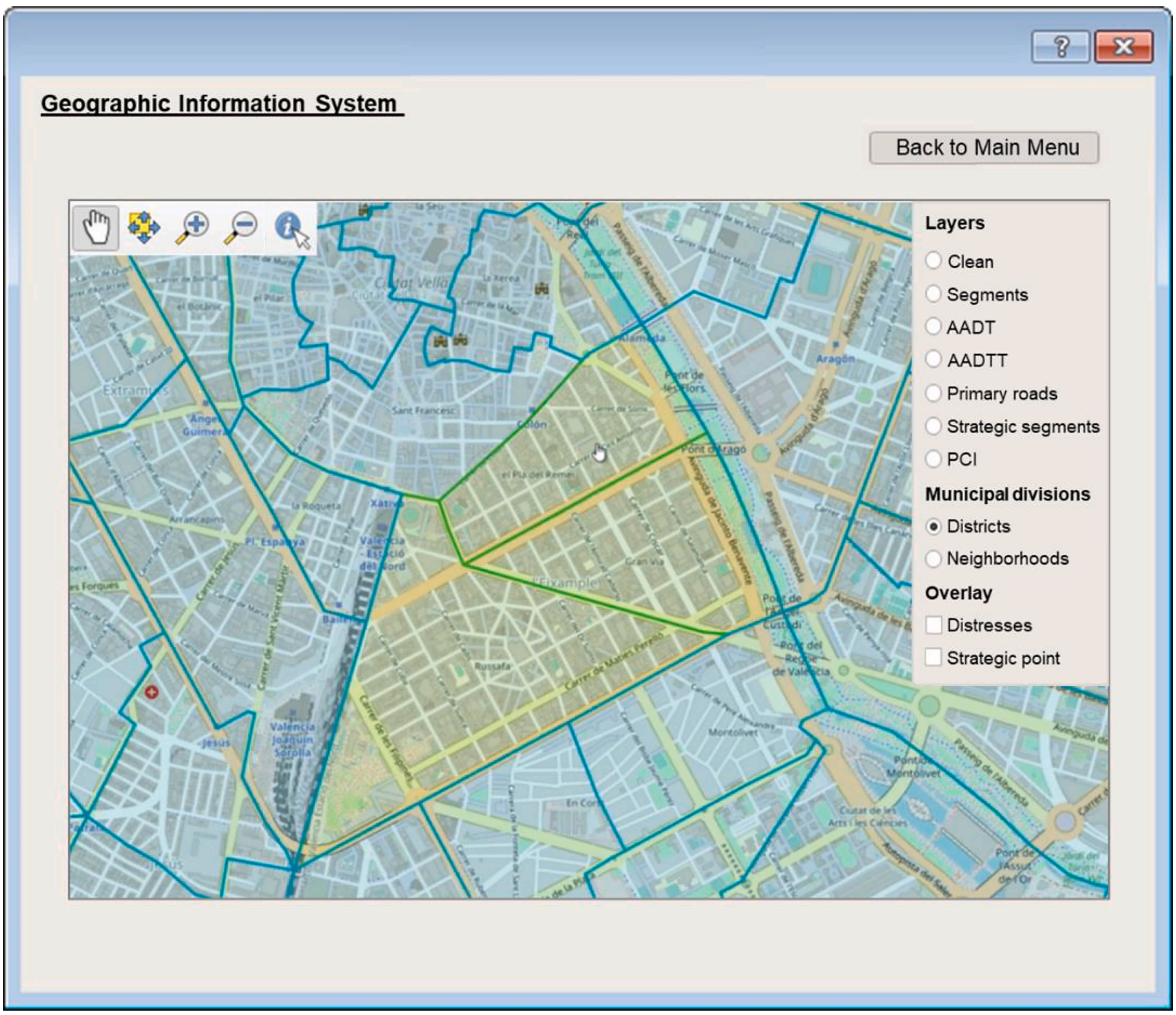


Fig. 6. Districts and neighborhood panel.

several primary roads essential for guaranteeing a proper road communication throughout the city.

Following the tool framework, the urban road network of Valencia was created using OpenStreetMaps database. Fig. 5 shows the road network on the city map. Traffic information was downloaded from the local administration. Then, the corresponding district was selected to perform the following modules. Fig. 6 shows the user interface for selecting the district. The district contains 489 segments.

The inspection module was performed for obtaining the images of the pavement. The inspection equipment recorded 700 min of videos, resulting in 600 k images. The videos and the GPS information were uploaded to the UM-PMS. The third module was processed for identifying, classifying, and quantifying the multiple pavement distresses through the convolutional neural networks. The distresses were assigned to the corresponding segments considering the GPS information. Fig. 7 shows the distresses displayed when selecting a road segment, indicating the type of distress, the severity and the quantity. Then, the Pavement Condition Index (PCI) was determined for each segment (Fig. 8).

Once the condition of the network was known, the user introduced the annual average temperature of the city to complete the information needed to perform the prediction model. In addition, the decision-making parameters needed as input data were completed. In this case, the parameters proposed by the expert panel were considered (Fig. 4).

Regarding the important segments, the railway station was selected as a strategic point considering a radius of 200 m. The important segments located inside the circle are shown in Fig. 9. Additionally, the primary roads were taken into account as strategic segments due to their primary role. Fig. 10 displays the segments considered as primary road based on the OpenStreetMaps information.

Finally, all the previous information was used for identifying the optimum timely maintenance. Three optimizations were performed to analyze the results. The first optimization considered the five objectives equally weighted and 5 years of planning horizon ($S_{mo,T5}$), which would be equivalent to a government period. The second optimization also analyzes a short-term period of 5 years, but considering the cost as the only objective for a mono-objective optimization ($S_{cost,T5}$). This optimization is performed to obtain information on the cheapest solution to maintain the condition threshold. Note that although the mono-optimization only considers the cost objective, the results of the other objectives are calculated to allow comparison with the multi-objective results. For the third optimization, a cost optimization is carried out considering an analysis period of 20 years ($S_{cost,T20}$). The objective of this analysis is to obtain the cheapest long-term solution. Therefore, $S_{mo,T5}$ is compared to $S_{cost,T5}$ and $S_{cost,T20}$ to verify whether multi-objective optimization improves the most economical solution both in the short term and in the long term.

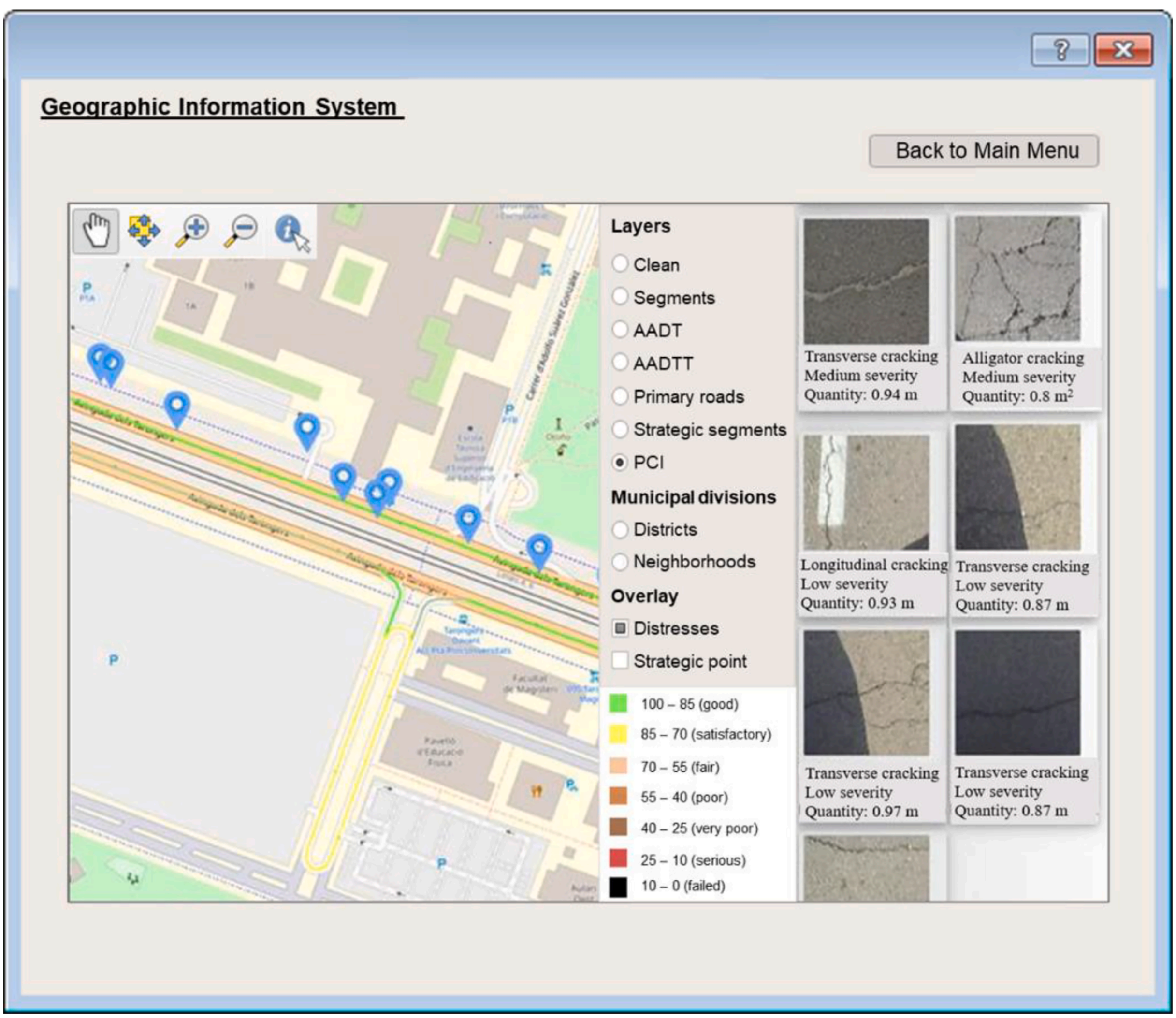


Fig. 7. Classification and quantification of distresses of a segment.

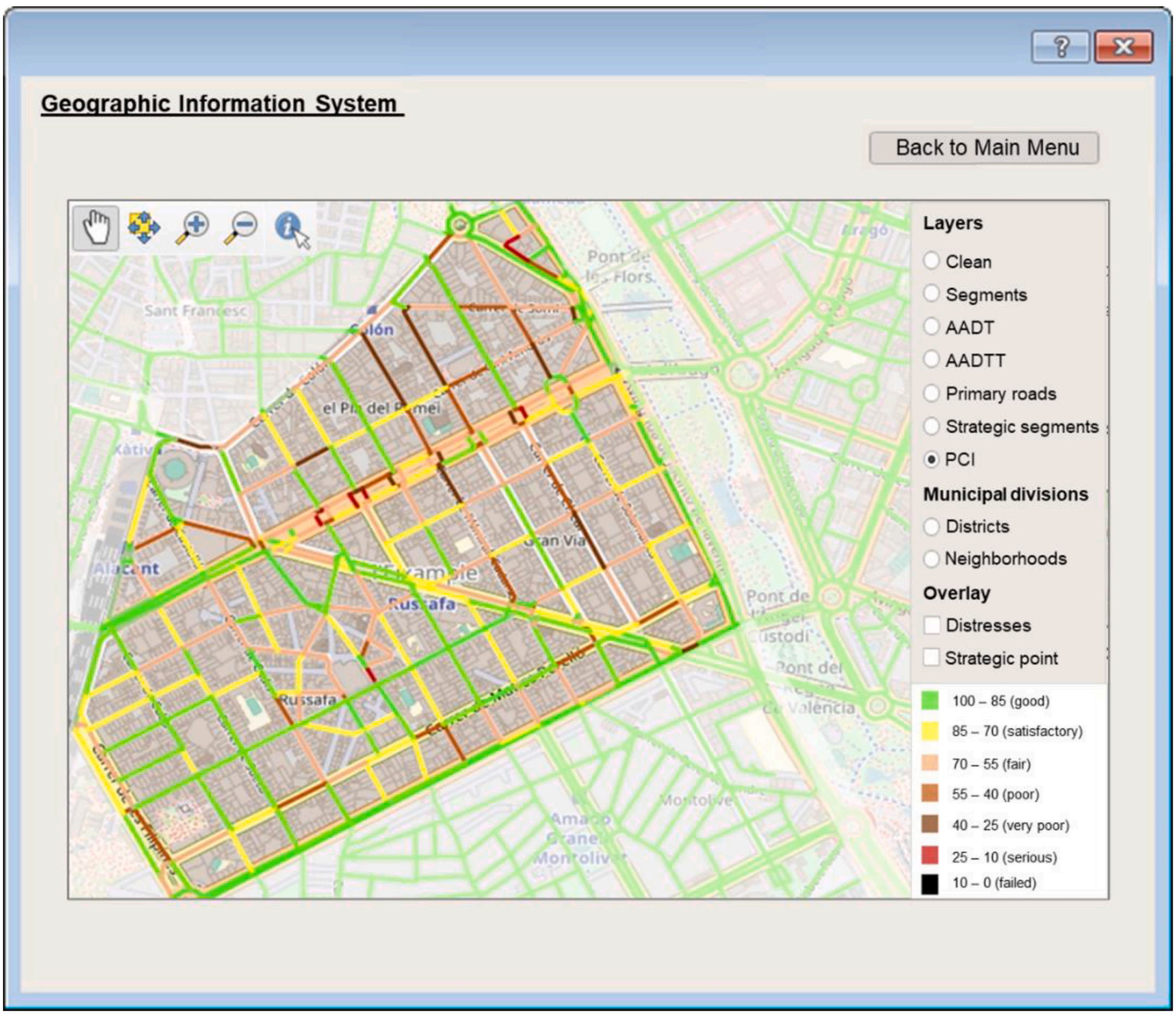


Fig. 8. PCI results.

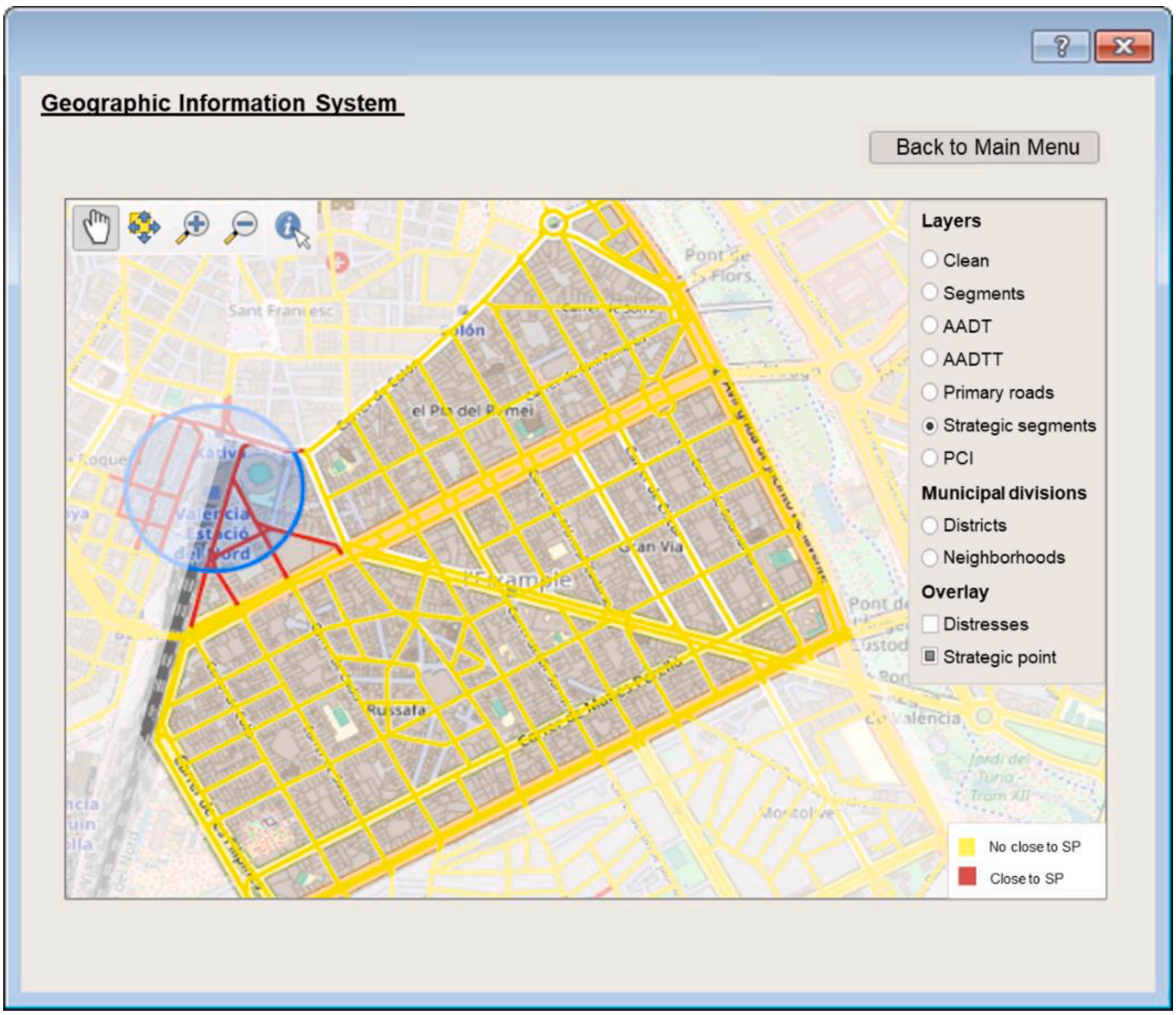


Fig. 9. Important segments due to their proximity to a strategic point.

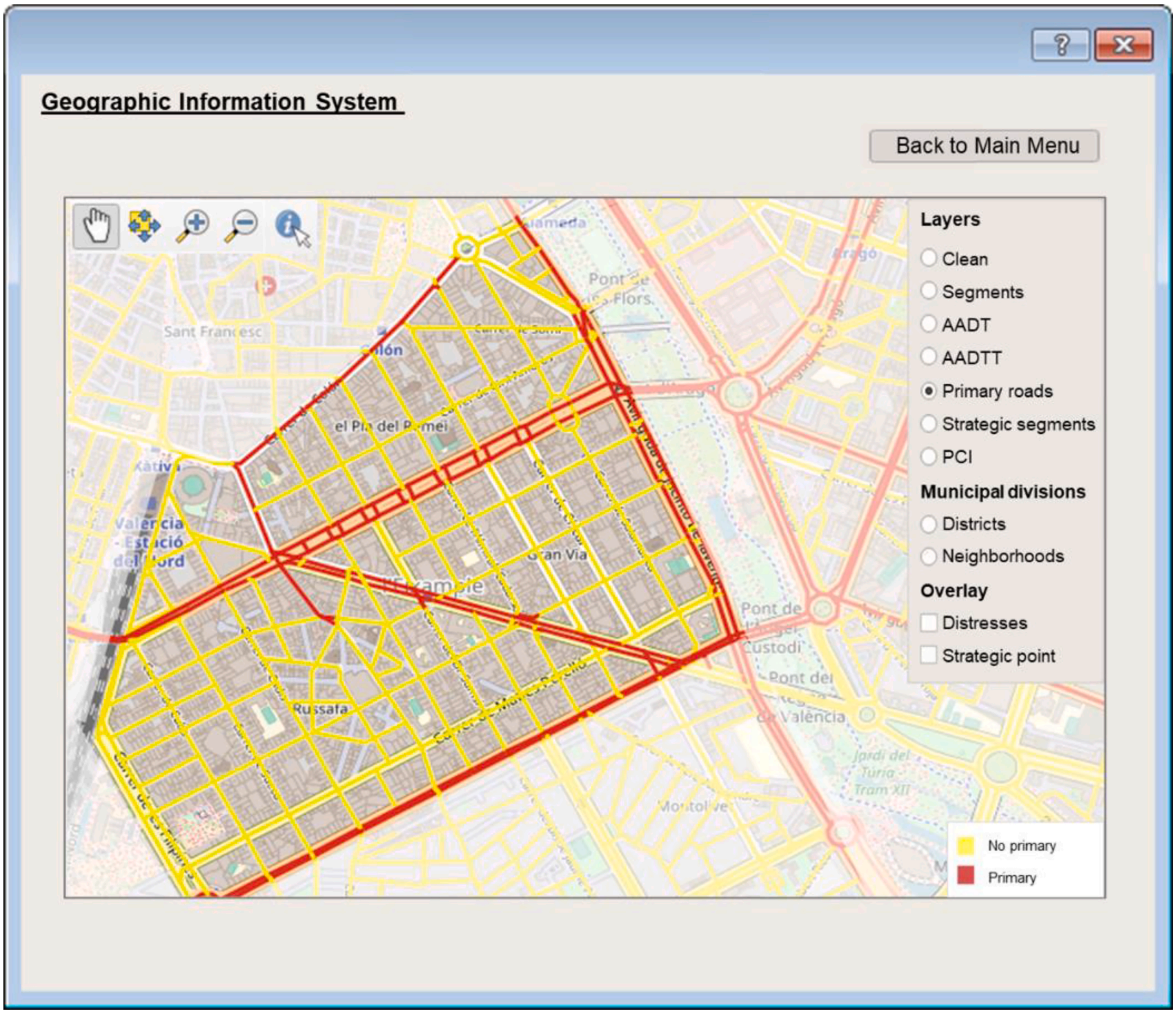


Fig. 10. Primary roads.

The optimization module provides the best maintenance schedule and the results of the objective functions. Table 2 shows the results of the objective functions: value of the cost (V_{cost}), value of the CO_2 emission (V_{CO2}), value of impact on users (V_{users}), value of contribution to the social development (V_{sd}), and value of improvement of network condition (V_{cond}). These normalized values represent the extent to which these objectives are achieved. A value of 1 represents the best possible value of the objective considering all possible maintenance plans during the planning horizon. Results show that $S_{mo,T5}$ achieve values between 0.62 and 0.84, indicating that the multi-objective optimization of the five objectives finds a compromise solution that effectively meets the pavement management goals of urban networks. This result is compared to the mono-objective optimization of the cost ($S_{cost,T5}$). Results reveal that the mono-objective optimization finds a good solution for the three first objectives leaving the value of social development and network condition below 0.10, which means that these objectives are closer to the worst possible values. However, when the analysis period is increased ($S_{cost,T20}$), V_{sd} and V_{cond} obtain better results. One of the major findings of this analysis is that, although the values of social development and network condition are inversely proportional to cost optimization, these values increase with extending the analysis period even though cost is the only optimization objective. This is explained by the fact that cost-optimization considering 5 years only performs the necessary maintenance treatments, leading to a poor network that would need a costly treatment after the analysis period. However, when 20 years are considered as the planning horizon, the analysis reveals that the best long-term solution is to take some preventive interventions to avoid the network deterioration and thus, costly long-term treatments. This strategy improves the network condition and encourages the social development.

Table 2
Value of the objectives.

	V_{cost}	V_{co2}	V_{users}	V_{imp}	V_{cond}
$S_{mo,T5}$	0.82	0.83	0.84	0.70	0.62
$S_{cost,T5}$	1.00	1.00	1.00	0.09	0.06
$S_{cost,T20}$	1.00	1.00	0.97	0.64	0.48

To analyze the impact of these solutions, the following performance indicators are calculated: the average annual cost (AAC), the average annual emissions (AAE), the average annual treatments (AAT), the average minimum PCI reached by the important segments ($APCI_{min,imp}$), and the average PCI at the end of the analysis period ($APCI_f$). Findings indicate that $S_{mo,T5}$ improves $APCI_{min,imp}$ and $APCI_f$ compared to the $S_{cost,T5}$ (Table 3). The $S_{mo,T5}$ results are in line with $S_{cost,T20}$, as both have a similar number of annual treatments. These preventive interventions improve the network condition. However, $S_{mo,T5}$ improves the condition of the important roads and achieves annual costs and emissions below those obtained with long-term optimizations. As a conclusion, the multi-objective optimization of the five objectives proposed can be used to guarantee a sustainable maintenance plan. In addition, results indicate

Table 3
Performance indicators.

	AAC (€)	AAE (kg CO_2)	AAT	$APCI_{min,imp}$	$APCI_f$
$S_{mo,T5}$	172017.94	545264.93	43.20	69.33	73.10
$S_{cost,T5}$	114081.65	388027.83	16.00	55.47	62.16
$S_{cost,T20}$	223266.08	630957.64	46.60	53.76	76.56

Table 4
Sensitivity analysis of the weights: deactivation of each objective (DOi).

	AAC (€)	AAE (kg CO_2)	AAT	$APCI_{min,imp}$	$APCI_f$
DO1	**38%**	38%	35%	9%	12%
DO2	37%	**39%**	35%	9%	12%
DO3	22%	23%	**30%**	8%	9%
DO4	−28%	−29%	−40%	**−16%**	−16%
DO5	−33%	−34%	−48%	−15%	**−19%**

that considering all five objectives in a short-term optimization do not compromise the long-term results.

Previous results considered the five objectives equally weighted. However, the weights should be adapted to local needs. To illustrate the impact of each objective on the results, a sensitivity analysis was performed deactivating each objective (Table 4). For example, when cost objective is deactivated (DO1), this objective is not considered in the optimization ($w_1 = 0$). Results show that, in this case, the best maintenance solution is 38% more expensive, but $APCI_{min,imp}$ is improved by 9% and $APCI_f$ by 12% because the number of maintenance treatments is increased. Regarding the environmental objective, if this objective is not considered (DO2), the result is very similar to the previous one with a 39% increase in emissions. Therefore, these two objectives should be taken into account when looking for more cost-effective solutions with lower emissions, while minimizing the possible deterioration of the road condition. On the other hand, objective 3 seeks to minimize the impact on road users with more preventive treatments and less road closure. For this reason, if this objective is not considered (DO3), the number of treatments is increased by 30%, and also, these treatments are less preventive. Thus, the first three objectives work in a similar way, although objective 3 prioritizes preventive actions that reduce the impact on users and improve the road condition. The last two objectives perform inversely, if objective 4 is not taken into account (DO4), $APCI_{min,imp}$ is reduced by 16%. The last objective focuses on improving the overall condition, so if it is not considered (DO5), the final condition of the network worsens by 19%. In conclusion, these last two objectives should be considered to improve the condition of the network, despite increasing the number of treatments with their consequent increase in cost and emissions.

Therefore, this approach demonstrates that the integration of environmental objectives can reduce the emissions of the maintenance program by 10 to 30% (Torres-Machi et al., 2017; Zhang et al., 2013). In addition to the economic, environmental, and performance objectives that are commonly used in pavement optimization studies (Chong et al., 2018; Saha & Ksaibati, 2018; Sun et al., 2020; Torres-Machi et al., 2018), UM-PMS proposes two new objectives: impact on users and contribution to the social development. The sensitivity analysis shows that impact on users can be used when the urban manager aims to reduce the impact on users due to the closure of the road, while maintaining an appropriate condition of the road network. Regarding the contribution to the social development, this objective enables the urban manager to find an optimum maintenance program that improves the condition of important road segments. The optimization that includes the five objectives ($S_{mo,T5}$) yields similar results to the best long-term optimization ($S_{cost,T20}$) and in addition improves the condition of the important roads and reduces annual costs and emissions.

4.1. Conclusions, limitations, and further research

This paper presents the framework of an urban pavement management system. This tool integrates the needs of the different components of an urban PMS overcoming the existing limitations for an automatic and objective assessment of the pavement condition. Firstly, GIS provides a visual interface platform for integrating the urban road map with the information needed for the pavement management. Then, pavement inspection is carried out by an automatic equipment composed by a video camera. The frames of the video are processed by two CNN to classify and quantify the urban distresses. This information is used to estimate the PCI in each road segment. The following module predicts the pavement condition through the planning horizon according to the road characteristics. Finally, MCDM and multi-objective methodologies are designed in a comprehensive manner to provide the optimal maintenance plan according to the decision-maker preferences. MIVES technique is used for introducing the urban manager parameters through the value functions. Then, the maintenance optimization identifies the optimum timely maintenance considering economic, environmental, social, and performance objectives.

The application of the UM-PMS to a case study shows the potential of the tool to provide the information needed for an accurate management of the pavement. Furthermore, the results of optimization illustrate that the five objectives considered for the multi-objective optimization are convenient to obtain a sustainable maintenance plan that reduces maintenance costs, CO_2 emissions, and impact on users, while improving the performance of the network, especially in those segments that have a higher level of importance to guarantee the social function of the urban network. Findings also indicate that this multi-objective optimization can determine a short-term plan for a government period in line with the best long-term results.

Therefore, this paper presents an automatic and easy tool to help urban managers in the pavement maintenance management, providing accurate data for controlling and planning the urban road network. This tool can be adapted to the requirements of the administration, changing the planning horizon, the weights of the objectives or the treatment preferences.

Regarding the limitations, UM-PMS is defined for flexible pavements located in urban areas. The prediction model and the pavement treatments are adjusted to these characteristics. In addition, the inspection technique is limited to 50 km/h to guarantee an appropriate image quality. When blurred images are provided, the CNNs might not identify and quantify the distresses accurately. CNNs are trained to detect the most common distresses in urban road networks, which are longitudinal cracking, transverse cracking, alligator cracking, raveling, potholes, and patching. Therefore, other types of distresses are not assessed by the tool.

Further research is needed to inspect arterial roads driving at a speed of more than 50 km/h. Additionally, other types of distresses can be considered collecting more images and training the CNNs to detect and quantify these distresses. Regarding maintenance optimization, Bayesian approaches can be incorporated to perform model updates when initial conditions change. Finally, additional work is needed to include more objectives considering the needs of other international countries.

CRediT authorship contribution statement

Tatiana García-Segura: Conceptualization, Methodology, Software, Writing – original draft. **Laura Montalbán-Domingo:** Conceptualization, Methodology, Validation, Writing – original draft. **David Llopis-Castelló:** Methodology, Software, Validation, Writing – original draft. **Amalia Sanz-Benlloch:** Formal analysis, Validation, Writing – review & editing. **Eugenio Pellicer:** Conceptualization, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Eugenio Pellicer reports financial support was provided by Spanish Ministry of Science and Innovation.

Data availability

Data will be made available on request.

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