



Exploring New Computational Strategies for Managing Maintenance Activities of Airport Pavement Systems

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Received: 16 March 2022 / Revised: 22 July 2022 / Accepted: 31 July 2022
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Abstract

In this paper, the optimization of the maintenance management problem regarding airport pavements is addressed by developing a series of fast computational procedures whose rationales pursue both practical and economical objectives. Particularly, the study involves the design of five new heuristic algorithms replicating different management strategies that can be undertaken by the airport managers in a certain time horizon for reducing the pavement maintenance costs while considering the impact on the service level of the airport. Each algorithm works on the basis of a preliminary computational framework that has a twofold scope: (i) selecting the pavement portions to be maintained during the provided time horizon. (ii) using a K-means method based on three well-known performance indicators, which, namely, are Residual Life (RL), International Roughness Index (IRI) and Pavement Condition Index (PCI), to group the selected portions into homogenous clusters named work-zones. To evaluate the effectiveness and the efficiency of the proposed optimization algorithms in coping with the maintenance programming problem under investigation, an extended design of experiments based on international airport regulations has been arranged. The obtained numerical results revealed that no single strategy can be selected as the most performing in terms of cost and quality conditions of the pavements. To make robust the numerical results, a sensitivity analysis is conducted to evaluate the influence of the total cost of maintenance on runway length and number of sections. However, the results obtained in this study provide a series of managerial implications, further expanding the research contribution.

Keywords Airport · Pavement management · Optimization · Heuristic algorithms · Clustering

1 Introduction

Although pavement management is a well-established issue, the need of smart maintenance strategies for managing the airport infrastructures has been capturing a growing interest among practitioners and academics over the years. Nowadays, all airport stakeholders need to adopt a maintenance program preserving the flight infrastructures in conditions of safety, functionality and efficiency [1]. To assure safety and passengers' comfort, the quality of the pavement becomes

crucial and a proactive pavement maintenance allows to extend the service life in a cost-effective way [2].

In this context, an Airport Pavement Management System (APMS) concerns all those activities involved in providing pavements at an adequate service level, ranging from data collection to the programming and execution of maintenance intervention [3]. This iterative system evaluates maintenance alternatives over a specified analysis period, on the basis of predicted values of quantifiable pavement attributes and predetermined criteria, then provides decision makers with optimum strategies [4]. It is a dynamic process that, starting from the cataloging of the pavement infrastructures, is capable of: (i) identifying their current quality conditions and assessing the deterioration rate over time, (ii) determining the thresholds to detect the necessity of a maintenance intervention, (iii) define the Maintenance and Rehabilitation (M&R) activities assigning the relative costs of the activities. The APMS, therefore, compares the various maintenance alternatives, establishes priorities and allocates funds

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on the basis of management targets and interconnected objective functions [5].

The choice of the objective functions could consider technical, economic, operative and environmental impacts of the investments. However, the costs and benefits are currently based only on economic objective function or monetary valuation which reduces the effectiveness of the process [6]. Focusing on the optimization in pavement management, the process of finding the best way of using available resources is required [7], without violating any of the constraints. Typically, optimization leads to strategy analysis for estimating medium-term budget requirements for the preservation of the airside infrastructures at network level. Furthermore, it is useful for preparing a multi-year maintenance problem at project level under budget constraints, in which the activities connected to the pavement sections requiring interventions are identified.

In the past, the choice of M&R activities was based on questionnaire surveys and historical practices [8]. Nowadays, computer-based intelligent M&R approaches are needed to efficiently and effectively cope with the pavement maintenance issue [9]. For this reason, in recent years, various algorithms have been developed for pavement management systems, however, most of them cope with the road field and the network level. Consequently, the optimization process mainly concerned the determination of the budgets and the general allocation of resources, through an overall strategy of the paving network [10]. On the other hand, the research studies carried out at the project level are fewer, especially with reference to the infrastructural characteristics of the airports.

In fact, the road pavement M&R optimization problem has been addressed from various points of view over the years. For example, Meneses and Ferreira [11] presented the development and implementation of a multi-objective decision-aid tool (MODAT) which considers the minimization of agency and user costs and the maximization of the residual value of pavements. A multi-objective optimization problem for pavement maintenance and rehabilitation strategies on network level was discussed by Elhadidy et al. [12], using genetic algorithms, to minimize the action costs and maximize the condition for used road network. The problem of the budget allocation was addressed by France-Mensah and O'Brien [13]. With the aim of optimizing the use of the available budget, Augeri et al. [14] used a decision-rule preference model for identifying the best combination of maintenance actions in a planning urban pavement maintenance. A development of an optimization framework for network-level pavement maintenance and rehabilitation planning considering the uncertain nature of pavement deterioration and the budget with a multistage stochastic mixed-integer programming model was proposed by Fani et al. [15] to find the optimal plan.

García-Segura et al. [16] have incorporated the uncertainty of pavement deterioration into pavement management optimization. Recent studies have addressed the M&R planning problem linked to user costs [17, 18]. Either way, as regards the computational techniques, due to the complexity of the problem, many authors have adopted a heuristic technique in their solution [19, 20, 21].

As mentioned before, in comparison to the road pavement management systems, the APMS has not captured the same attention by literature so far. Although the management approaches are similar, the strategies underlying the airport pavement are certainly different. Airport pavements, in fact, are subjected to peculiar operative condition and higher safety levels are needed [22]. It is clear that the need to carry out an unscheduled intervention on a runway with the consequent obligatory closure of the same has extremely different impacts compared to the management of a similar intervention on a roadway for which it is necessary at most to take into account a reduction of traffic capacity. In this regard, Ansarilari and Golroo [23] developed a hybrid approach of Markov Chain and supervised multi-objective genetic algorithms at network-level, while Moayedfar and Sajjadifard [24] analyzed the prioritization process using the widely spread software PAVER®. Liu et al. [25] highlighted the importance of using preventive maintenance for the management of the flight infrastructures, discussing a possible set of indexes and the corresponding thresholds to support the decision-making for a specific moment in project level. De Moura et al. [26] illustrated a review on the airport pavement evaluation systems for maintenance strategies development, pointing out various considerations regarding the limitations and possible development of future research. A comparative study of probabilistic and deterministic methods for the assessment of direct and indirect costs in a life-cycle cost analysis for airport pavements is recently discussed by Babashamsi et al. [27].

The present research focuses on the maintenance management optimization of airport pavements developing a series of fast computational procedures whose rationales pursue both practical (airport operative conditions) and economical objectives. Specifically, this paper illustrates different M&R optimization strategies, because it is believed that there is not a unique optimal strategy, but several possible solutions that can be undertaken by the airport managers according to their needs. For this reason, this study explores five constructive algorithms replicating different management strategies that can be undertaken by the airport managers for reducing the pavement maintenance costs while considering the impact on the service level of the airport.

The proposed approach first analyzes the parameters influencing the pavement deterioration according to ASTM D-5340-20 [28]. Once the areas having similar pavement conditions have been identified, the application of a cluster

function leads to the grouping of similar adjacent objects into the same clusters [29], hereinafter called work-zones. This choice is strategic, as it mitigates possible operating restrictions given by possible runway closures caused by the execution over the time of the M&R activities in close pavement portions with similar maintenance necessities. In fact, one of the novelties of this research proposal is that the grouping of the areas into work-zones is conducted using a K-means method based on three well-known performance indicators, which in turns considers adjacency among the pavement portions as a further clustering constraint.

In this way, the independent variables of the optimization problem are identified and the performance of each maintenance strategy over a certain time horizon can be assessed. From this point of view, to the best of our knowledge, this paper represents the first attempt to investigate the airport pavement maintenance management distinguishing the planning period from the control time one, as follows. The first indicates the time interval in which to provide any M&R activities to be carried out, the second is defined with the aim of ensuring the quality level of the airport pavement above the critical thresholds. This choice avoids the situation, where any M&R activities performed at the end of the planning period is not able to generate any beneficial effect on the pavement maintenance program.

To validate the effectiveness and the robustness of the proposed optimization algorithms, an extended design of experiments has been arranged and a numerical–statistical comparison among the five algorithms has been carried out to highlight the different managerial implications connected to the choice of each different optimization heuristic process. Furthermore, a sensitivity analysis has been executed whose results become a key element for all airport managers in the identification of the optimal M&R strategy to conduct in a given airport pavement runway.

This paper is organized as follows. The following paragraph introduces a list of notations to support the readability of the problem statement and the computational procedures as well. Section 2 highlights the structure of the proposed problem through the problem statement, also reporting the objective function. Section 3 illustrates the assumptions of the problem and the decoding procedure. In Sect. 4, there is a detailed description of the methodologies used for both the clustering function and the constructive heuristic algorithms. Section 5 demonstrates the robustness of the proposed approaches through a design of experiments including a large set of runways. In this regard, it is considered essential to report the results of the sensitivity analysis and the numerical comparison between the scenarios. Section 6 focuses on the managerial implication and, finally, Sect. 7 deals with the conclusions, limitations of the study and future research directions.

1.1 Notations

The following symbols are used in this paper:

a	Violation exponent of the objective function
$A(w)$	Extension of work-zone w [m^2]
$A(z, s) = (H \times L_s)/Z_s$	Extension of sub-section z in section s [m^2]
C_t	Total maintenance costs [€]
$C(x)$	Unit cost of type x M&R activity [€/m ²]
H	Runway width [m]
$I = \{0, 1, \dots, N\}$	Set of M&R activities
IRI	International Roughness Index performance measure [m/km]
IRRI	International Reciprocal Roughness Index performance measure [km/m]
J	Cluster label
$k = 1, \dots, K_{z,s}$	index of sample-units in sub-section z of section s
$K_{z,s}$	Number of sample-units of sub-section z in section s
L_s	Length of section s [m]
N	Maximum number of available M&R activities
$P^q(x_{wt})$	The q th performance measure of work-zone w at time t after the maintenance intervention $x_{w,t}$
$P^q_{k,z,s}(t)$	Type q performance indicator of sample-unit k of sub-section z in section s at time t
$P^q_{v,z,s}(t)$	Type q performance measure of work-zone v of sub-section z in section s at time t
$P^q_{w,z,s}(t)$	Type q performance measure of critical work-zone w of sub-section z in section s at time t
PCI	Pavement Condition Index
$q = 1, \dots, Q$	Index of performance indicator
Q	Number of performance indicators
R	Expected number of clusters
RL	Residual Life performance measure [year]
$s = 1, 2, \dots, S$	Index of sections
S	number of sections
$t = 0, \dots, T$	Index of the time period
T	Planning time horizon [year]
T_c	Control time horizon [year]
t_w	Time at which at last one quality constraint is violated at work-zone w [year]
t_w^{min}	Minimum time period at which at last one performance measure violates the threshold Th_q [year]

Th_q	Critical threshold for performance measure q
$u_{k,z,s}$	Sample-unit k of sub-section z in section s
$U_{v,z,s}$	Number of sample-units into the v th work-zone of sub-section z in section s
$v = 1, \dots, W_{z,s}$	Index of work-zone of sub-section z in section s
viol	Constraint violation
$w = 1, 2, \dots, W$	Index of critical work-zones
W	Number of critical work-zones
$W_{z,s}$	Number of work-zones of sub-section z in section s
$w_{z,s}^v$	Work-zone v of sub-section z in section s
X	Matrix $T \times W$ whose elements represent the different M&R activities assigned to work-zone w at time t
$x_{wt} \in I$	Solution variable: M&R activity assigned to critical work-zone w at time t
$z = 1, 2, \dots, Z_s$	Index of sub-sections in section s
Z_s	Number of sub-sections in section s

2 Problem Statement

The proposed APMS problem focuses on the runway infrastructure. According to ASTM D-5340-20 [28], the airport infrastructure under study can be represented as a single branch with flexible pavement, subdivided into S sections s ($s = 1, 2, \dots, S$). Based on the definition of section [30], various factors are considered for the process of dividing branches into sections, including pavement structure, construction history, traffic, pavement rank, drainage facilities and shoulders, condition, and size. For each section, let Z_s be equally extended pavement portions z ($z = 1, 2, \dots, Z_s$), specifically defined for this study and hereinafter denoted as sub-sections, with area $A(z, s) = (H \times L_s)/Z_s$, being H the runway width and L_s the length of section s (see Fig. 1).

The sub-sections represent bands of a section s having different degradation rate. More specifically, in this study it is assumed that the runway infrastructure is subjected to dissimilar stresses depending on the load given by the passage of the aircraft landing gear. In this way, the areas concerned to the passage of the main landing gear of the aircraft are more differentiated, as they could be subject to a faster deterioration. However, any sub-section z may present a non-uniform deterioration condition in all its extension; thereby, each sub-section z of a section s is discretized into $K_{z,s}$ smaller asphalt pavement portions known as

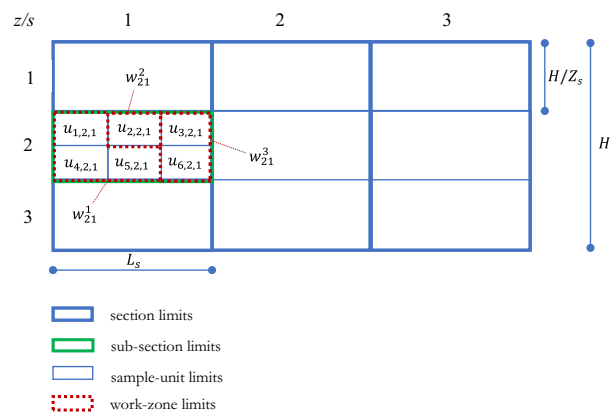


Fig. 1 Airport pavement schematization

sample-units k , for which a uniform deterioration condition can be assumed and whose size is equal to $450 \pm 180 \text{ m}^2$ [28]. Let us denote with $u_{k,z,s}$ the k th sample unit of sub-section z in section s . It is worth pointing out that, being the sub-section width a constant (i.e., H/Z_s , where H is the runway width and Z_s is the number of sub-sections in section s), every sub-section z of a certain section s holds the same number of sample units $K_{z,s}$, which in turn depends on the ratio between the extension of the sub-section z in the section s , $A(z, s)$, and the sample-unit size as mentioned earlier. Whenever an airport pavement management program has to be developed, a series of Q performance indicators have to be monitored along a certain planning time T , to assure the expected quality level of the overall pavement until the end of that period, at least. Hence, for each sample-unit, $P_{k,z,s}^q(t)$ ($q = 1, \dots, Q$) performance measures that identify the quality level of that pavement portion for the sample-unit k of sub-section z in section s at time t ($t = 1, 2, \dots, T$) can be evaluated. In general, every performance indicator is strictly connected to a deterioration curve [31] function that outlines the way a given quality measure varies along the time [32].

At time zero, i.e., to identify an effective M&R program, the quality conditions of the runway can be accurately described by the performance indicator values $P_{k,z,s}^q(0)$ for each sample-unit k . Although the sample units are featured by different types of performance indicators, denoting distinct quality condition, grouping them with each other could be useful for reducing the number of pavement portions to be included into the M&R program and the problem complexity as well. To this end, this paper utilizes a well-established K-means method to identify sample units with similar pavement deterioration condition on the basis of pre-established performance indicators and cluster levels (J), as detailed in the subsequent paragraphs.

A group of adjacent sample-units having a similar joint performance measure at time zero are specifically defined for this study as work-zones, to represent the operational areas

in which to conduct the M&R activities (see Fig. 1). Since each work-zone may involve only adjacent sample units, the K-means clustering algorithm has been properly adapted to fulfill such restriction. In fact, starting from the subdivision into cluster label of the sample units, those adjacent to the same cluster have been merged as work-zones. The variable $w_{z,s}^v$ denotes the v th work-zone ($v = 1, \dots, W_{z,s} | W_{z,s} \leq K_{z,s}$) of sub-section z in section s , being $W_{z,s}$ the total amount of work-zones in that sub-section. Figure 1 works as an illustrative example in which Sect. 2 of Sect. 1 holds the following work-zones: $w_{2,1}^1 = \{u_{1,2,1}, u_{4,2,1}, u_{5,2,1}\}$, $w_{2,1}^2 = \{u_{2,2,1}\}$, $w_{2,1}^3 = \{u_{3,2,1}, u_{6,2,1}\}$, being the number of work-zones ($W_{z,s} = 3$) lower than the number of sample-units ($K_{z,s} = 6$) and $U_{v,z,s}$ the number of sample-units into the v th work-zone.

Once a work-zone v is constructed, the related q th performance measure $P_{v,z,s}^q(0)$ at time zero is equal to the worst value among the provided $U_{v,z,s}$ sample-units into the v th work-zone of sub-section z in section s . Equation 1 formally fixes the q th performance indicator $P_{v,z,s}^q(0)$ of work-zone v including a number of $U_{v,z,s}$ sample-units:

$$P_{v,z,s}^q(0) = \min_{j=1, \dots, U_{v,z,s}} P_{j,z,s}^q(0) \tag{1}$$

After the arrangement of the work-zones and the definition of the Q performance indicators for each of them, it is possible to predict the decay of the pavement performance through the implementation of specific functions [32]. Whenever the performance indicator of a work-zone $P_{v,z,s}^q(t)$ achieves a certain critical threshold (Th_q) at a certain time t , the corresponding work-zone is identified as critical and requires M&R activities to satisfy the provided quality requirements in the entire time horizon. Continuing in this fashion, a set of W critical work-zones throughout the sections are detected and, again, such pavement portions of area of work-zone w $A(w)$ will be the only ones needing a maintenance action within the planning horizon T . Actually, any intervention executed at the end of the planning time horizon T would not be capable of generating any benefic effect on the M&R programming problem. Therefore, a larger planning period named control time horizon T_c ($T_c > T$) has been introduced in this study to properly assess the effects of any maintenance intervention accomplished even at the end of the planning time horizon. Hence, the quality requirements of all critical work-zones have to be assured over the control time horizon T_c , while the M&R activities to be executed for optimizing a certain objective function, e.g., the minimization of the total maintenance cost, has to be fulfilled within the planning time horizon T .

To identify a feasible maintenance program, capable of assuring the minimum quality level for each type of performance indicator at the end of the control period (i.e., $P_{v,z,s}^q(t) \geq Th_q, \forall t \leq T_c$), several kinds of M&R airport actions [23] may be undertaken on each critical works-zone.

Every intervention is configured as a discrete variable and the greater the benefic effect of a given intervention on the performance measures, the higher the cost. Hence, the optimization issue consists in a constrained combinatorial problem, that is to select the most suitable maintenance actions to be executed on the critical work-zones at certain times as to minimize the total maintenance cost, while assuring the minimum quality level for each performance measure. In light of the aforementioned considerations, the variable X of the problem can be configured as follows:

$$X = \begin{bmatrix} x_{11} & \dots & x_{1T} \\ \dots & x_{wt} & \dots \\ x_{W1} & \dots & x_{WT} \end{bmatrix} \tag{2}$$

where W is the set of critical work-zones, T is the planning time horizon and $x_{wt} \in I$ is the kind of intervention at time t on the critical work-zone w , being $I = \{0, 1, \dots, N\}$ the set of available M&R actions. Notably, $x_{wt} = 0$ means that no action is undertaken for the generic critical work-zone and the related cost is zero. If $C(x_{wt})$ is the maintenance cost associated to maintenance action x_{wt} on work-zone w at time t , then the optimization problem can be formalized as follows:

$$\min C_t \tag{3}$$

s.t.

$$P^q(x_{wt}) \geq Th_q, \forall q \in 1, \dots, Q; w = 1, \dots, W; t = 1, \dots, T_c \tag{4}$$

$$C_t = \sum_{w=1}^W \sum_{t=1}^T C(x_{wt}) \tag{5}$$

where C_t is the total maintenance cost to be minimized and $P^q(x_{wt})$ is the q th performance value of work-zone w at time t after the maintenance intervention x_{wt} . Specifically, to assure the expected quality level of the airport pavement at the end of the control time horizon T_c , for each work-zone w , each $P^q(x_w)$ performance indicator value must be greater than or equal to the provided threshold limit Th_q , being the index $x_w = x_{w,1}, x_{w,2}, \dots, x_{w,T_c}$.

3 Evaluating a Solution of the M&R Problem

Evaluating how different M&R interventions (executed in specific critical work-zones in identified time periods) affect the quality of the runway and the total maintenance cost is a key-issue to develop an effective optimization method for the APMS problem under investigation. The following sections deal with the general assumptions of the proposed model and

a detailed explanation of the leading components driving any solution evaluation.

3.1 Measures of Performance and Critical Work-Zones

In this study we consider $Q = 3$ well-established performance indicators, namely, the Residual Life ($P^1 = RL$), the International Roughness Index ($P^2 = IRI$) and the Pavement Condition Index ($P^3 = PCI$). The choice to consider the three indicators just mentioned depends on whether they are performance measures usually used to investigate flight infrastructures through periodic instrumented surveys [33]. However, the same approach can be used regardless any other performance indicator.

With exception of IRI, the higher both RL and PCI the better the residual life and the surface pavement condition of the runway portion under analysis. To make IRI consistent with the trend of the previous performance measures, in the present approach the reciprocal IRI indicator, from now on denoted as IRRI, has been adopted for the subsequent considerations. Taking into account the type of infrastructure examined in this study, 20 years can be assumed as the best pavement conditions in terms of RL [34]. As for IRI, the best can be assumed equal to 0.7 m/km based on ASTM E1926-08 [35], and the best IRRI equal to 1.43 km/m, accordingly. Finally, the PCI value corresponding to the best pavement condition can be set to 95, in accordance with ASTM D5340-20 [28]. Actually, all these indicators are connected to specific decay functions [32], which are capable of delivering information on the deterioration condition achieved by each pavement portion as the time elapses. Similarly, such discrete functions allow assessing and monitoring the quality/deterioration conditions of any pavement work-zone after a certain maintenance action has been carried out. The periodic estimation of the pavement condition avoids the unexpected occurrence of distresses [36], as these could tend to happen suddenly due to environmental impacts and traffic loading [37]. Since predictive degradation models are not easily transferable from one airport to another and considering that this study does not want to be specific for a single airport, theoretical time-dependent decay models are used.

Specifically, the deterioration models of *RL* and *IRRI* are linear, while a non-linear relationship is assumed for *PCI*, as follows [38]:

$$RL(t) = RL(t - 1) - 1 | 0 \leq RL(t) \leq RL_{opt} = 20 \text{ years } \forall t \quad (6)$$

$$IRI(t) = IRI(0) + 0.4 \times t \quad (7)$$

$$IRRI(t) = 1/IRI(t) \quad (8)$$

$$PCI(t_0 + t) = -0.14(t_0 + t)^3 + 2.28(t_0 + t)^2 - 15(t_0 + t) + 100 | PCI(t) \geq 0 \quad \forall t \quad (9)$$

where t_0 is a time reference value necessary to assess the PCI indicator at time zero.

Hence, the q th performance measure of a certain pavement portion at a time t corresponds to the values of the related decay function at that time. Since in every sub-section adjacent sample-units having a similar initial deterioration status are combined into a work-zone, for this study it is considered that the q th aggregate performance measure is equal to the worst (i.e., the minimum) value among the sample units within that work-zone, that is

$$P^q_{v,z,s}(t) = \min_{k=1, \dots, U_{v,z,s}} P^q_{k,z,s}(t), \forall t = 0, \dots, T_c \quad (10)$$

In case one of the q performance indicators of the v th work-zone at a certain time t (i.e., $P^q_{v,z,s}(t)$) is lower than the critical threshold (Th_q), the quality level of that portion is considered as inadequate and a constrain violation occurs. All work-zones for which a constraint violation occurs in the control time horizon are denoted as critical work-zones. Therefore, $w^v_{z,s} \forall v = 1, \dots, W_{z,s}$ is a critical work-zone $\Leftrightarrow P^q_{v,z,s}(t) < Th_q, z \in \{1, \dots, Z_s\}, s \in \{1, \dots, S\}, q = 1, \dots, Q, t = 1, \dots, T_c$. The number of work-zones over the entire runway is equal to W , being $w = 1, \dots, W$ the index of the critical work-zones to be subjected to M&R activity.

3.2 Effect of M&R Activities

In this research, five types of M&R activities ($I = \{0, 1, 2, 3, 4\}$) have been taken into account [38] (see Table 1). As a consequence, being X configured as a 2-dimensional solution, every element may assume an integer value in the range [0, 4]. Each type of intervention can be distinguished in terms of thickness, unit cost and expected incremental (only for RL) or restoring (for IRI and PCI) effect. Of course, the so-called do-nothing activity (type 0) disregards any M&R action and coincides with $x_{w,t} = 0$. The deep structural activity (type 1) is applied on the work-zone w at time t when $x_{w,t} = 1$. It is the most impactful and costly activities provided in this paper. It is capable of increasing the RL value by 20 years (Florida Department of Transportation (FDOT)) [34] and restoring IRI (IRRI) and PCI to 0.7 m/km (1.43 km/m) [35] and 95 [28], respectively. Two intermediate interventions named *intermediate structural* (type 2) and *surface structural* (type 3) are lower impact alternatives even though no difference emerges under both IRI and PCI restoring viewpoint. Interestingly, the *functional* activity provides a significant effect only for IRI and PCI indicators, while no benefic consequence arises from the type-4 activity on the

Table 1 M&R activities

M&R activities	Thickness	$C(x)[\text{€}/\text{m}^2]$	Effects		
			ΔRL [year] $Th_{RL} =$ 0-year	IRI [m/km] $Th_{IRI} = 3.60$ m/ km	PCI $Th_{PCI} =$ 25
Do-nothing (type 0: $x_{w,t} = 0$)	–	–	Do nothing		
Deep structural (type 1: $x_{w,t} = 1$)	65 cm	168.89	20	0.7	95
Intermediate structural (type 2: $x_{w,t} = 2$)	35 cm	102.04	5	0.7	95
Surface structural (type 3: $x_{w,t} = 3$)	15 cm	46.94	2	0.7	95
Functional (type 4: $x_{w,t} = 4$)	5 cm	18.05	0	0.7	95

RL indicator. Basically, the higher the thickness the higher the unit cost. Table 1 also reports the critical threshold values representing the minimum quality limits for each performance indicator, namely, $Th_{RL} = 0$ -year, $Th_{IRI} = 3,60$ m/km ($Th_{IRRI} = 0.278$ km/m), $Th_{PCI} = 25$ [35]. In addition, the unit cost ($\text{€}/\text{m}^2$) of each activity is indicated by $C(x)$ as $x_{w,t}$ may assume only integer values in $[0,4]$.

It should be noted that the characteristics of the pavement and, consequently, the effects of the M&R activities depend on the materials used during the activities [39]. For this study, it is considered a package composition consisting of the following materials: Cement Bound Granular Mixtures (CBGM) for subbase course (30 cm), High Modulus Asphalt Concrete (HMAC) for base course (20 cm) and binder one (10 cm), and Splittmastix Asphalt (SMA) for wearing course (5 cm). Hence, type 1 activity provides the stabilization of the subbase course and the resurfacing of the base, binder and wearing courses, thus restoring the pavement to optimal structural and functional conditions. Type 2 activity includes the resurfacing of base, binder and wearing courses, which means improvement of the pavement structure and restoration of the functional conditions. Only a little increase in the residual useful life is expected after the application of type 3 activity, which still allows to restore the optimal conditions from the functional point of view through a resurfacing of binder and wearing courses. Finally, type 4 activity allows the restoration of the wearing course, but no impact on the residual life occurs. As expected, more invasive maintenance activities require longer time for their execution. For this reason, activities 1 and 2 significantly impact on the airport operations. Activities 3 and 4, on the other hand, are the ones that can be completed in a short time (i.e., a few hours), and

therefore, they can be adopted when a lower impact on the airport operations is desirable.

It is important to point out that the rules for applying a particular M&R activity depend on the type of strategy adopted. In this framework, the optimization algorithms support the decision-making process, finding some of the possible combinations of interventions to be carried out during the planning period. More specifically, for this study the type of approach is managed from the use of heuristics algorithms, reported in Sect. 4.

3.3 Decoding Procedure

Starting from a generic solution X (See Sect. 2), the decoding procedure determines the total cost C_t due to the provided M&R activities applied on the critical work-zones during the planning horizon T . Besides, such computational procedure is responsible for the assessment of the pavement quality conditions generated by the X maintenance actions at the end of the control period T_c . Whether, for one or more work-zones, the activities provided by solution X are not capable of assuring a performance measure $P^q(t)$ greater than the quality threshold Th_q , a constraint violation occurs and a penalty value to the total cost is added. To better explain the rationale of the proposed decoding procedure, a proper pseudo-code of the Solution Decoding Algorithm (SDA) is provided at the end of this section.

Similar to other studies [40, 41], the adopted time unit is equal to 1 year and only one intervention can be applied in a given year.

Pseudo-code: Solution Decoding Algorithm**Step 1:** Initialization:
$$X, A(w), \forall w = 1, \dots, W; P_{w,z,s}^q(t) \forall t = 0, \dots, T_c, w = 1, \dots, W, z \in \{1, \dots, Z_s\}, s \in \{1, \dots, S\}, q = 1, \dots, Q | Q = 3; Th_q, \forall q = 1, \dots, Q; T, T_c; C_t = 0, c(x), a;$$
Step 2: Deployment of M&R activities in X :

Assign maintenance interventions to each critical work-zone w at time t according to X and update the performance measures $P_{w,z,s}^q(t)$ at every time period t by using the provided decay functions.

Step 3: Objective function evaluation:

Once the Q performance measures of each work-zone have been adjusted according to the M&R activities provided by solution X , total cost and constraint violations are computed.

*Step 3.1 Total cost computation:***For** $w = 1, \dots, W$ **For** $t = 1, \dots, T$

$$C(x_{w,t}) = c(x_{w,t}) \times A(w)$$

$$C_t = C_t + C(x_{w,t})$$

End**End**

Where, $A(w)$ is the extension of the w -th work-zone.

Step 3.2 Evaluation of constraint violation: $viol = 0$ **For** $w = 1, \dots, W$ **For** $t = 1, \dots, T$ If $P_{w,z,s}^q(t) \leq Th_q$ then

$$viol = viol + (Th_q - P_{w,z,s}^q(t))$$

End**End***Step 3.3 Objective function calculation:*

$$f(X) = C_t \times (1 + viol)^a$$

Where, a can be considered as a violation amplification exponent.

Step 4: Stop algorithm

4. Optimizing the APMS problem

4 Optimizing the APMS Problem

Optimizing a combinatorial problem as the APMS under investigation entails the selection of the more suitable maintenance actions to be placed along the provided time horizon, while respecting a series of constraints regarding the quality of the runway. Figure 2 depicts the flow-chart concerning the three-stage optimization methodology proposed in this paper, which can also be used in the road sector with the appropriate calibrations regarding the performance measures, quality thresholds and types of M&R activities. First, the input data about the runway deterioration conditions (Th_q), the dimension of the runway (H, L_s), and other information related to the decision-making variables (T, T_c) have to be preliminary set. In this phase, the runway is divided into S sections and each of them into Z sub-sections. Consequently, the $K_{z,s}$ sample-units within each sub-section are identified and the performance in terms of deterioration condition is assigned to each of those. In brief, at time zero, the performance measures $P^q(0)$ are assigned to all sample-units and the quality thresholds are set, as well.

Subsequently, the use of a clustering method, conducted before the launch of the heuristic algorithm, allows to generate the work-zones of area $A(z, s)$. Handling work-zones instead of sample units is a common practice [42] to rationalize both traffic and maintenance operations, reducing the

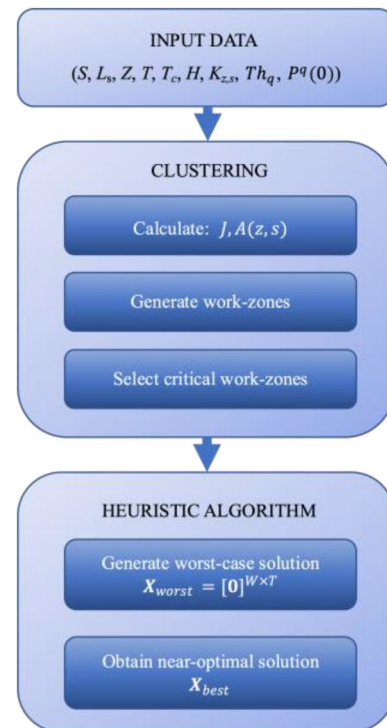


Fig. 2 Flow-chart of the optimization method

Table 2 Strategies used in the heuristic algorithms implemented for this study

Heuristic	Strategy
Heuristic 1	For each critical work-zone, application of a single M&R activity
Heuristic 2	For the critical work-zones requiring type-1 and type-2 activities, merging of them in the minimum year
Heuristic 3	For all critical work-zone, application of all the activities in the most frequent period
Heuristic 4	For each critical work-zone, implementation of a single M&R activity or, if more convenient, of two less invasive activities
Heuristic 5	For each critical work-zone, implementation of only light M&R activities as type-3 and type-4 activities

risk of disservices for the stake-holders as well. Once the clusters in terms of work-zones are configured, the heuristic algorithm constructs the near-optimal solution, i.e., the M&R programming problem, with the aim of minimizing the total maintenance cost while respecting a series of quality constraints (i.e., thresholds) of the runway along the provided time horizon. The following paragraphs deal in detail with both the clustering method and the different heuristics proposed for optimization purposes.

4.1 Clustering Method

Adopting a clustering method for gathering the pavement portions having similar deterioration conditions to reduce the problem dimension is a well-established approach. Tsai et al. [43] used a spatial search algorithm based on the fuzzy c-mean clustering. Yang et al. [44] employed a spatial clustering algorithm using fuzzy c-mean (FCM) for the Georgia Department of Transportation to determine the terms of the pavement conservation project by analyzing the assessment of pavement condition at the segment level. The clustering algorithm for pavement maintenance problems based on the K-means is another widespread method to be implemented in several data analysis tools [45, 46]. However, recent studies propose new clustering methodologies, such as the K-Prototype algorithm, which consists in an improvement form of the K-Means and the K-Mode clustering algorithm [47]. Among the new approaches it is worth mentioning the clustering-based Ant Colony Optimization, to improve the decision-making and clustering analysis in pavement asset management [48] and the clustering-PageRank algorithm (CPRA), based on historical big data. They integrate the cluster analysis and a topic-sensitive PR algorithm, the latter being an algorithm originally developed for sorting the value of web pages [9].

Since the present research does not focus on the development of any new clustering method, this paper utilizes a well-established K-means method to select the sample units to be gathered into work-zones. In brief, it aims to combine the adjacent sample units with similar pavement deterioration conditions, properly selected on the basis of the three provided performance metrics, namely, RL, IRI and PCI.

To group similar items of the data set together, the K-means algorithm uses a fixed number of centroids (termed as target number k); depending on its features, every element is assigned to one of the centroids such that the in-cluster sum of squares is minimized. As for the APMS problem under investigation, the data set elements coincide with the sample units and clusters of sample units are configured as work-zones. Since each work-zone may involve only adjacent sample units, the K-means clustering algorithm has been properly adapted to fulfill such restriction.

In detail, sample units within every sub-section with uniform characteristics at time zero $P_{k,z,s}^q(0)$ are grouped into homogeneous clusters. The K-means clustering has been executed by means of the machine learning tool in Matlab R2021®. The number of clusters has been set to three on the basis of what experienced by Rejani et al. [45] for an urban road context, who stated that the optimum number of groups is found by satisfying two conditions:

1. Within class variance should be minimum or between class variance should be maximum.
2. Each cluster should contain at least 5% of the entire pavement portions.

4.2 Heuristic Algorithms

Since the solution of this problem consists of a 2-dimensional integer array holding the types of maintenance activity to be carried out at a certain time, such problem can be configured as a combinatorial problem. In addition, it also belongs to the class of constrained optimization problems as discussed in Sect. 2. Note that the computational complexity of combinatorial problems strongly increases with the problem size, i.e., with the number of decision variables. In addition, the dynamic structure of the proposed APMS problem, in which decay functions and maintenance activities interact with each other during the planning horizon, make this problem hard to be mathematically modelled and solved in a reasonable time. To solve such complex combinatorial problem, numerous studies revealed that several optimization techniques can be deployed for generating effective M&R preventive maintenance program. In this regard,

Xiao et al. [49] provided a decision-making tool for planning and scheduling of M&R activities, at both the project and network level, applying an evolutionary-based optimization technique, namely, Genetic Algorithm. Gao et al. [50] used the parametric method to simultaneously optimize pavement condition improvement and budget utilization and its effectiveness and efficiency is studied and demonstrated through a case study using the Dallas District Pavement Real World data set. Coyote optimization algorithms and genetic algorithms have been applied by Naseri et al. [51] to enhance the network condition and minimize CO₂ emissions. In light of these contributions, we decided to develop a series of tailor-made heuristic algorithms based on different airport managerial rationale (see Table 2), for the identification of an effective solution through a constructive criterion in a reasonable time, even for large-sized issues. The following sub-sections describe in detail the behavior of each heuristic reported in this study. However, it is useful to underline that these strategies, which are also shared with some airport managers, could be suitably calibrated without changing the structure of the algorithms.

4.2.1 Heuristic 1

The rationale behind this constructive heuristic algorithm (H1) lays on the identification of the earliest time t_w^{min} at which the execution of a proper activity $\tilde{x} \in I$ to be applied to every critical work-zone w is able to eliminate any constraint violation (i.e., $P_w^q(t) \geq Th_q, \forall q = 1, \dots, Q, t = 1, \dots, T_c$). In detail, for each w , the earliest time period $t = t_w^{min}$ at which any $P_w^q(t)$ performance indicator exceeds its respective critical thresholds Th_q is selected. Then, the less costly maintenance intervention (\tilde{x}) capable of eliminating or reducing at most the constraint violation is selected and applied on that work-zone w at that time ($x_{w,t} = \tilde{x}$).

It is worth pointing out that, for H1, only a single activity \tilde{x} can be applied along T_c to each critical work-zone. As result, this heuristic tends to select a single impactful intervention, for a total rehabilitation, thus renouncing to any alternative strategy, such as the execution of less-costly activities in different time periods. The computational pseudo-code of H1 is in Appendix A.

4.2.2 Heuristic 2

The second heuristic (H2) is an evolution of H1 as it aims to concentrate all type-1 and type-2 rehabilitation activities at the same year to minimize the impact on the airport operations. Let X^{H1} be the solution from H1. The algorithm first identifies the set Γ of time periods t in which type-1 or type-2 M&R activities occur in one or more work-zones and then it finds the minimum time value t_{min} . From now on, the algorithm continues similar to Heuristic 1. In fact,

every critical work-zone w is selected and if $t_w^{min} \neq t_{min}$ then the less-costly activity (\tilde{x}) to be started at time t_{min} instead of t_w^{min} and capable of assuring zero constraint violation is selected ($X^{H2} = \tilde{x}$). The algorithm continues in this fashion until the whole set of critical work-zones has been elaborated. A pseudo code of Heuristic 2 algorithm is reported in Appendix A.

4.2.3 Heuristic 3

Heuristic 3 (H3) aims to identify the year within the planning period at which the M&R activities on the critical work-zones have to be carried out. Specifically, this strategy focuses all M&R interventions at the same year so as to minimize their impact on the airport operations. The first objective to fulfill is to identify the most suitable time period in which all M&R activities should be performed on the critical work-zones. To this end, the algorithm starts finding the times at which the quality constraint is violated for each work-zone w , hereinafter denoted as t_w . Hence, the most suitable time period for executing the M&R actions is configured as the most frequent one (i.e., t_{freq}) among the t_w values. Hence, the less costly M&R activities capable of assuring zero constraint violation in the time interval $[T_c - t_{freq}]$ are selected for the critical work-zones. Since it may happen that $t_w < t_{freq}$ for some work-zones, the less costly M&R activities able to assure a constraint violation equal to zero in the time interval $[t_{freq} - t_w]$ are applied to those work-zones. The pseudo-code of H3 is in Appendix A.

4.2.4 Heuristic 4

The heuristics presented earlier tend to perform only one M&R activity per work-zone during the time horizon. However, sometimes this is not enough and it may happen that even the most impactful activity fails to meet the quality requirements related to Th_q . Furthermore, in some cases it could be more convenient to consider two less invasive activities instead of one with a higher cost. Such a smooth strategy could lead not only to relevant cost savings, but also to a lower impact on the daily airport operations. To this end, the fourth heuristic algorithm (H4) can be configured as a modified version of H1, as it assigns to each work-zone w a lower impact M&R activity at time t_w^{min} and then, at a later time t_w , it places another maintenance intervention able to fully satisfy the quality constraint requirements along the entire control time horizon. In detail, let w be a critical work-zones and t_w^{min} the time to place an M&R intervention. The determination of t_w^{min} is explained in Sec. 4.2.1. Once the time period t_w^{min} is detected, instead of searching the less-costly and most impactful activity able to guarantee no constraint violation (i.e., $viol=0$), this heuristic selects the subsequent one, i.e., the one assuring a lower impact, even

Table 3 Designs of experiments at varying WL

Factors	DOE1			DOE2			DOE3		
WL	30 [m]			45 [m]			60 [m]		
B	4			6			8		
Levels	1	2	3	1	2	3	1	2	3
L [m]	1500	1600	1700	2300	2500	2700	3000	3300	3600
S	7	9	11	9	11	13	11	13	15

if it yields a constraint violation greater than zero. Then, the same search mechanism is repeated, this time considering the effect of the M&R activity placed earlier. A new $t_w^{min} \leq T$ time period is selected and this time another type of intervention avoiding any constraint violation at a minimum cost is chosen for being inserted into the X^{H4} heuristic solution.

The algorithm continues in this fashion until all work-zones have been managed. The corresponding pseudo-code is in Appendix A.

4.2.5 Heuristic 5

Especially in the airport context, it could happen that a basic need of the management staff is to mitigate any risk of interruption of the airport operations. Consequently, it is necessary to carry out activities that can be completed in a short time (i.e., a few hours). Such scenario regards the implementation of only light M&R activities as type-3 and type-4 interventions. However, both of the aforementioned maintenance interventions need a short time to be carried out and, as a result, they are strictly recommended when the regular operativity of the runway has to assured, also minimizing the related disservice to all stakeholders. The pseudo-code of the proposed constructive heuristic algorithm, which makes use of only type-3 and type-4 activities, is reported in Appendix A.

The heuristic solution can be easily constructed by following the steps of the pseudo-code and reveals that a cost-effective M&R programming problem can be generated only by implementing type-3 actions on the provided work-zones.

5 Experiments and analysis of results

To assess both the effectiveness and the computational efficiency of the proposed heuristic algorithms, a benchmark of test-cases has been generated and, subsequently, a comprehensive experimental analysis has been performed.

5.1 Design of experiments

To evaluate the ability as well as the robustness of each heuristic in solving the proposed APMS constrained optimization problem, a large number of airway pavements should be

Table 4 Ranges for generating sample unit initial conditions

Indicator/ percent- age	80%	20%
RL	[3, 20]	[0, 20]
IRI	[0.7, 2.4]	[0.7, 4]
PCI	[54.4, 95]	[0, 95]

investigated. To this end, a Design of Experiments (DOE) based on a multitude of randomly generated flexible runways having different sizes has been pursued. The following lines deal with the rationale behind the generation of the aforementioned airway scenarios. To assure a sufficient level of diversity regarding the runway size, pavements 30, 45 and 60 m wide have been considered. For each width level (WL), a specific DOE has been configured, in which two distinct factors, namely, the runway length (L) and the number of sections (S), are the independent variables. In addition, it is worthy to specify that, for each width level, a fixed number of bands B having constant width (i.e., $H = WL/B$) is provided. Being H the width of every sub-section throughout the provided sections, the number of sample units, pertaining to each sub-section, comes out of the extensions reported in ASTM D-5340–20 [28]. Specifically, in this study, each sample-unit width is equal to 7.5 m, while its length is set to 50 m, for a total area of 375 m². Table 3 reports the structures of the three designs of experiments (DOE1, DOE2, DOE3), where the both L and S have been varied at three levels. Note that all the data are created in accordance with ICAO Annex 14 [1] Aerodrome Reference Code and ICAO Minimum Runway Width. Finally, a number of 100 different instances, i.e., runway configurations, have been generated for each DOE so as to give more robustness to the analysis of the obtained numerical findings. As a result, each DOE is based on 900 randomly generated runways (namely, instances). Considering that there are three DOEs and five alternative solving methods, i.e., constructive heuristics, a total number of 13,500 runs have been executed. The following sub-section deal in detail with the generation of the numerical instances and the parameter setting for the clustering method, as well.

5.1.1 Generation of Numerical Experiments

The numerical generation of any instance is carried out as follows. Each section length L_s is randomly generated subject to the limits that L_s is a multiple of the sample unit length (i.e., 50) and $\sum_s L_s = L$. Hence, being both B and the sample unit size known a-priori, each sub-section configuration is defined. Now, each sample-unit is randomly initialized in terms of deterioration conditions. To this end, considering $Q=3$ types of deterioration metrics (i.e., RL, IRI and PCI), the current conditions, i.e., the performance measures for each sample-unit at time zero $P_{k,z,t}^q(0)$, are randomly drawn according to the following criterion: for each performance indicator, 80% of the sample units may achieve the related critical threshold after a time horizon equal to $T/2$, so only 20% of sample units can be critical in the time interval $[0, T/2]$ (see Table 4). In this way, it is ensured that the condition of the airport runways is not excessively degraded, making it possible to represent an actual process in which runway management has already been constantly conducted over the years.

In accordance to the common airport practice, in this study the planning time horizon T and the control time horizon T_c are set to 6 and 8 years, respectively, for each scenario problem [24]. Particularly, since H5 makes use of only type-3 and type-4 M&R activities, it may happen that for some critical work-zones the RL threshold limit at the end of the control time horizon T_c is not satisfied. As a result, H5 heuristic can be classified as a temporary strategy in which any inertia-effect during the additional control time horizon T_c can be ignored. For this reason, to be fair in the comparison among heuristics, an 8-year planning time horizon T is considered for H5, while no control time horizon is considered ($T_c=0$).

5.2 Comparison of Heuristics

This section reports the numerical results achieved by each heuristic algorithm as the problem size changes. To measure the difference of performance of the provided heuristics in terms of total cost Ct , the Relative Percentage Deviation [52] has been considered:

$$RPD_{h,s,l,i} = \frac{C_{h,s,l,i} - \min_{h \in H1..H5} C_{h,s,l,i}}{\min_{h \in H1..H5} C_{h,s,l,i}} \times 100; \quad \forall s, l, i \quad (11)$$

where $C_{h,s,l,i}$ means the total cost reached by the h th heuristic, for coded section level s ($s \in \{1, 2, 3\}$), coded length level l ($l \in \{1, 2, 3\}$) and instance i ($i \in \{1, \dots, 100\}$).

Table 5 allows the reader to evaluate the difference of performance among the provided heuristics under a series of key performance indicators (KPIs) based on the RPDs

computed length level, over 300 instances (100 runways varied at three s levels), namely: median (*med*), mean (*ave*), standard deviation (*sigma*), maximum (*max*) and number of best local optima (*n_opt*). In addition, the average number of critical work-zones W_{ave} has been reported in the same table. Looking at the latter indicator, it appears that the problem complexity in terms of number of critical work-zones to be tackled slightly grows with both the runway length (L). Bold values in Table 5 highlight the best values for each KPI, considering that, with exception of the standard deviation, all of them have to be minimized. It is clear that the most performing heuristic for the minimization of the total cost of maintenance is H4, regardless of L . The median RPDs assured by H4 are all equal to zero at varying L , and the mean values are significantly lower than those pertaining to the other heuristics with exception of H1, which appears as the best competitor. Actually, the numerical results related to H4 reveal high values in terms of maximum RPD (*max*) and relatively high standard deviation values (*sigma*); thus, it means that there are a few scenario problems in which another heuristic (likely H5 or H1) achieve a sensibly lower cost of maintenance. The number of optimal solutions related indicator, i.e., n_{opt} , further confirms the outperformance of H4. However, it is worth noting that H5 appears as the most suitable approach in about one-third of the investigated scenario problems, regardless of the runway length. In addition, there are a few instances in which H1 results the best maintenance policy to be adopted.

To assess the way each heuristic algorithm affects the provided performance measures (i.e., RL, IRI, PCI) along the time horizon, a further numerical analysis have been arranged. Particularly, such analysis aims at evaluating a series of KPIs (namely, mean, standard deviation, minimum and maximum values) on the aforementioned three quality indicators at the end of the planning time horizon, that is equal to six years. Hence, the objective of such analysis consists in evaluating the effectiveness of the proposed heuristics not only under the cost reduction point of view, but also in terms of pavement quality conditions after the provided M&R actions.

Similar to the previous RPD cost analysis, Table 6 shows the numerical results for each performance indicator and for each heuristic. Notably, every value in the table refers to the KPI computed on the mean RLs, IRIs and PCIs at the end of the planning time horizon, over the 300 instances pertaining to each L level, regardless of any specific S . As for example, 7.82 that is the first value in Table 6, indicates the average of 300 \overline{RL} values in the class problem with $L=1500$, being in turn each \overline{RL} the mean RL value over the critical work-zones of each instance. Looking at the bold values in Table 6, that indicate the best values for each KPI, it is clear that H2 is the best M&R policy under the residual life viewpoint. Despite L , heuristics H1, H3 and H4 are not

Table 5 Numerical results for different runways based on the RPDs

<i>L</i>	KPI	<i>W_ave</i>	H1	H2	H3	H4	H5
1500	Med		4.10	25.45	33.24	0.00	17.79
	Ave	74.25	10.83	30.94	31.00	7.11	26.52
	Sigma		17.26	19.90	26.14	16.74	32.58
	Max		129.37	145.14	129.37	123.94	196.91
	N_opt		4	0	0	212	84
1600	Med		3.58	21.92	4.75	0.00	13.65
	Ave	83.14	10.06	27.17	20.47	6.71	26.09
	Sigma		15.71	17.99	23.77	15.22	33.13
	Max		109.38	131.14	109.38	101.89	192.51
	N_opt		2	0	0	212	86
1700	Med		3.62	22.46	4.30	0.00	16.67
	Ave	87.14	9.76	27.47	19.26	6.47	25.79
	Sigma		17.68	19.67	23.97	17.11	31.11
	Max		182.09	198.82	182.09	172.13	258.69
	N_opt		2	0	0	210	88
2300	Med		4.35	24.85	35.69	0.00	16.58
	Ave	158.01	7.44	28.06	30.86	3.41	23.06
	Sigma		9.19	11.57	24.14	8.89	25.19
	Max		63.90	87.11	98.79	58.46	132.30
	N_opt		0	0	0	226	74
2500	Med		4.54	27.67	47.73	0.00	17.58
	Ave	165.09	8.18	30.24	35.29	3.84	23.35
	Sigma		11.42	12.33	23.78	11.09	25.23
	Max		136.38	144.27	136.38	128.40	206.44
	N_opt		0	0	0	226	74
2700	Med		4.34	24.78	48.77	0.00	15.79
	Ave	177.12	6.63	26.81	34.56	2.55	21.92
	Sigma		6.97	8.91	23.51	6.73	22.56
	Max		53.37	84.78	106.49	47.78	119.00
	N_opt		0	0	0	229	71
3000	Med		4.54	27.23	51.25	0.00	17.50
	Ave	256.43	4.46	27.32	39.64	0.00	17.56
	Sigma		0.84	4.47	20.68	0.00	1.67
	Max		6.33	43.67	59.32	0.00	23.18
	N_opt		0	0	0	300	0
3300	Med		4.36	25.98	51.87	0.00	17.36
	Ave	280.60	4.37	26.10	39.25	0.00	17.45
	Sigma		0.75	3.77	21.53	0.00	1.66
	Max		6.86	37.99	59.13	0.00	22.91
	N_opt		0	0	0	300	0
3600	Med		4.41	26.13	51.49	0.00	17.88
	Ave	301.60	4.44	26.47	36.41	0.00	17.87
	Sigma		0.74	3.92	22.75	0.00	1.52
	Max		6.82	39.65	59.03	0.00	22.35
	N_opt		0	0	0	300	0

Bold values are indicates that the best values for each KPI

so dissimilar in terms of RL, while H5, as expected, is the worst strategy to be adopted under this perspective. Since IRI tends to increase along the time, H5 emerges as the

maintenance strategy capable of assuring lower IRI values at the end of the planning time. Bold values in the IRI section of Table 6 highlight that adopting frequent type-3 and

Table 6 Performance indicators for different runways lengths

Indicator	KPI	\overline{RL}					\overline{IRI}					\overline{PCI}				
		H1	H2	H3	H4	H5	H1	H2	H3	H4	H5	H1	H2	H3	KPI	H1
1500	Ave	7.82	9.36	8.14	7.33	4.49	1.66	1.86	1.88	1.49	1.24	77.42	75.05	76.03	80.58	83.43
	Sigma	0.80	0.79	0.79	0.81	0.61	0.14	0.13	0.96	0.15	0.07	2.01	1.92	14.76	2.21	1.21
	Min	5.81	6.77	6.00	5.31	2.49	1.21	1.45	0.70	1.08	1.04	68.08	67.07	63.57	70.39	78.74
	Max	11.54	12.39	11.52	11.14	6.56	2.35	2.45	2.70	2.23	1.53	84.50	81.67	95.00	87.34	87.56
1600	Ave	8.30	9.72	8.47	7.82	4.19	1.73	1.92	2.28	1.57	1.23	76.45	74.24	69.92	79.48	83.42
	Sigma	0.79	0.78	0.73	0.76	0.63	0.14	0.14	0.80	0.14	0.07	2.10	2.03	12.27	2.13	1.14
	Min	6.42	7.56	7.05	5.82	2.18	1.27	1.58	0.70	1.15	1.06	67.32	65.95	63.57	69.69	80.68
	Max	12.23	12.98	12.22	11.99	5.91	2.42	2.53	2.70	2.29	1.41	82.67	79.11	95.00	85.38	86.50
1700	Ave	8.21	9.70	8.38	7.77	4.26	1.73	1.92	2.33	1.57	1.24	76.48	74.23	69.30	79.53	83.34
	Sigma	0.70	0.64	0.67	0.67	0.60	0.13	0.12	0.77	0.13	0.06	1.81	1.71	11.87	1.89	1.02
	Min	6.53	8.12	6.97	6.18	1.95	1.31	1.52	0.70	1.18	1.10	66.69	66.30	63.57	69.99	80.35
	Max	12.09	12.45	12.07	11.71	6.27	2.44	2.48	2.70	2.25	1.43	82.18	79.62	95.00	84.62	85.92
2300	Ave	7.49	9.14	7.85	6.97	4.54	1.62	1.84	1.74	1.44	1.25	77.87	75.36	78.26	81.46	83.40
	Sigma	0.54	0.52	0.57	0.54	0.45	0.09	0.09	0.97	0.09	0.05	1.32	1.30	15.11	1.44	0.76
	Min	5.99	7.50	6.35	5.38	3.25	1.33	1.57	0.70	1.12	1.10	74.37	71.86	63.57	77.36	81.42
	Max	8.97	10.60	9.37	8.17	5.71	1.86	2.07	2.70	1.70	1.37	82.20	79.25	95.00	86.56	85.93
2500	Ave	7.36	9.04	7.77	6.83	4.56	1.62	1.83	1.57	1.43	1.25	77.88	75.38	80.81	81.60	83.32
	Sigma	0.53	0.51	0.53	0.53	0.45	0.10	0.09	0.97	0.10	0.05	1.42	1.36	15.02	1.51	0.82
	Min	6.21	7.72	6.55	5.74	2.26	1.37	1.62	0.70	1.21	1.13	68.23	67.54	63.57	71.28	80.66
	Max	11.60	12.11	11.56	10.98	6.20	2.35	2.42	2.70	2.18	1.44	81.65	78.93	95.00	85.02	85.24
2700	Ave	7.36	9.02	7.79	6.81	4.59	1.61	1.82	1.57	1.41	1.25	77.98	75.51	81.08	81.78	83.42
	Sigma	0.44	0.45	0.48	0.44	0.45	0.08	0.09	0.98	0.09	0.05	1.28	1.29	15.24	1.36	0.78
	Min	5.98	7.84	6.45	5.36	3.25	1.40	1.61	0.70	1.18	1.13	74.35	71.87	63.57	78.00	81.10
	Max	8.59	10.66	9.27	7.99	5.75	1.85	2.07	2.70	1.64	1.37	81.36	78.92	95.00	85.66	85.17
3000	Ave	7.12	8.89	7.63	6.55	4.69	1.58	1.80	1.22	1.37	1.25	78.45	75.83	86.45	82.33	83.41
	Sigma	0.42	0.43	0.47	0.40	0.36	0.08	0.08	0.85	0.08	0.04	1.14	1.10	13.43	1.20	0.67
	Min	5.83	7.62	6.31	5.32	3.75	1.39	1.60	0.70	1.20	1.16	75.42	73.12	63.57	78.74	81.69
	Max	8.19	10.09	8.97	7.58	5.49	1.78	2.00	2.70	1.60	1.39	81.50	78.90	95.00	84.86	85.15
3300	Ave	7.19	8.94	7.72	6.61	4.64	1.59	1.81	1.26	1.39	1.25	78.26	75.67	85.90	82.09	83.40
	Sigma	0.37	0.40	0.45	0.37	0.34	0.07	0.07	0.88	0.07	0.04	1.01	1.02	13.84	1.05	0.64
	Min	6.20	7.66	6.40	5.66	3.53	1.41	1.63	0.70	1.21	1.14	75.34	72.34	63.57	79.30	80.92
	Max	8.11	9.98	9.23	7.63	5.66	1.78	2.05	2.70	1.57	1.39	80.71	78.21	95.00	84.84	85.31
3600	Ave	7.13	8.89	7.61	6.56	4.60	1.60	1.82	1.37	1.39	1.26	78.16	75.56	84.21	82.04	83.35
	Sigma	0.37	0.38	0.45	0.37	0.31	0.06	0.06	0.93	0.07	0.04	0.93	0.93	14.66	1.02	0.63
	Min	5.95	7.77	6.38	5.51	3.67	1.45	1.66	0.70	1.20	1.14	75.62	73.19	63.57	79.33	81.77
	Max	8.14	9.74	9.27	7.60	5.32	1.76	2.00	2.70	1.58	1.36	80.38	77.94	95.00	84.97	85.47

Table 7 Percentage of M&R action types for each heuristic algorithm

Heuristic/ M&R action type	ACT_1	ACT_2	ACT_3	ACT_4	ACT_tot
H1	0.17	0.18	0.14	0.52	175.93
H2	0.31	0.03	0.14	0.52	175.93
H3	0.14	0.18	0.14	0.54	248.88
H4	0.12	0.06	0.39	0.44	208.12
H5	0.00	0.00	0.49	0.51	246.72

type-4 interventions on the pavement favors better quality conditions in terms of IRI. Such a surprising result can be justified by the fact that many type-3 and type-4 actions are required on a given critical work-zone when an RL issue exists. Therefore, on the average, such approach tends to increase the quality conditions of the entire pavement under the IRI viewpoint. The consideration can also be deduced for the PCI indicator. Observing the last \overline{PCI} section in Table 6, it is clear that H5 is again the most suitable strategy. Due to its computational structure, heuristic H3 is able to assure the best results in terms of minimum IRI and maximum PCI at

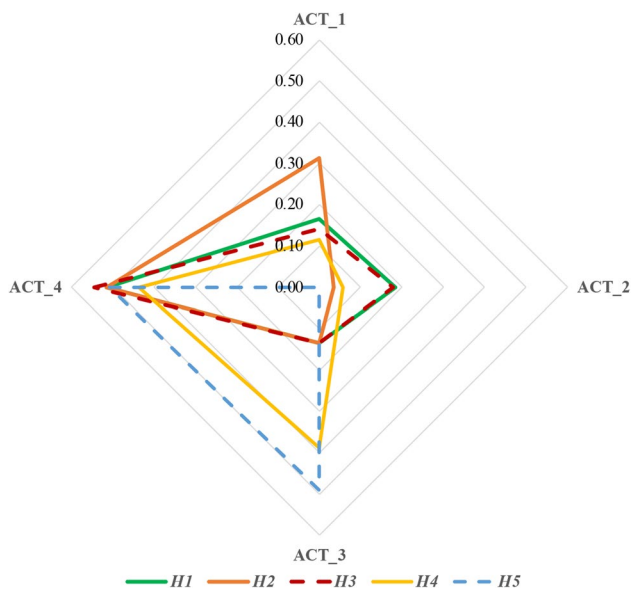


Fig. 3 Average number of interventions for each heuristic algorithm

the end of the planning horizon. However, it should be noted that H4 performs similar to H5 for IRI and PCI and similar to H1 and H3 as concerns the RL performance indicator.

To infer about the way each heuristic tackles the proposed APMS optimization problem, a numerical analysis that considers the mean quantity of maintenance actions, for each type of intervention, has been executed. Table 7 reports the percentage quantity of M&R interventions for each action type (ACT_1, ACT_2, ACT_3, ACT_4) over the entire set of numerical results, regardless of the specific runway length, i.e., considering 2700 scenario problems. The last column headed by ACT_tot refers to the number of actions adopted on the average by each heuristic. As expected, H1 and H2, which tends to apply only one intervention along the time horizon, make use of the minimum number of interventions to minimize the maintenance total. Conversely, the specific algorithm structures characterizing H3 and H5 imply a significantly higher number of maintenance actions equal to 248.88 and 246.72, respectively. Finally, it worth noting that H4, which appeared as the most performing strategy for the total cost minimization, accounts for the best compromise between the aforementioned alternatives in terms of ACT_tot indicator. The radar diagram in Fig. 3 depicts the numerical results from Table 7, thus allowing a straightforward insight on the results above mentioned. The main finding is that the radar shapes among the tested heuristics are quite dissimilar with exception of the ones related to H1 and H3. Although such diagrams are quite similar, Tables 5 reveal a remarkable difference of performance between the two heuristics in favour of H1. Hence, a different way of using the provided types of M&R actions would justify such a peculiar result.

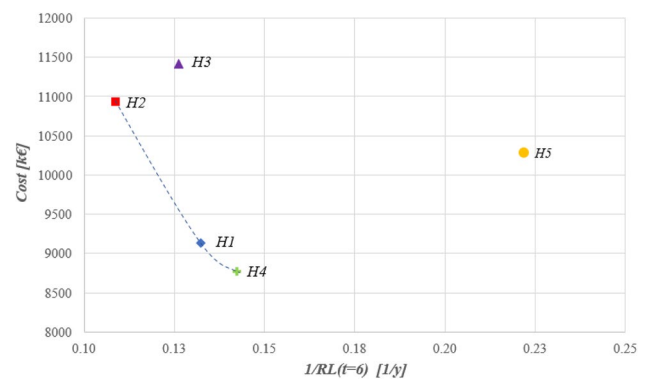


Fig. 4 Pareto diagram of heuristics

However, for each algorithm, the time for the implementation of the M&R activities is also estimated, highlighting that H5 is the least impacting at an operational level. An ideal match between Tables 5 and would allow assessing how much the tested heuristics are capable of keeping high the quality of the pavement conditions while reducing the total cost of maintenance. Under this perspective, to simultaneously evaluate both of the mentioned objectives, Fig. 4 shows a Pareto diagram in which the total cost in k€ is in the y-axis, while the reciprocal of the residual life ($1/RL$) at the end of the planning time ($T=6$) is in the x-axis. The choice to focus the analysis only on the RL performance indicator is given by the observation that, according to the assumptions of this study, the effect of a possible M&R activity on RL is not restorative but incremental; therefore, through RL, it is possible to verify the trend of the structural pavement conditions over the years for the different heuristics. Specifically, the average values of C_i and $1/RL$ over the entire data set have been computed for each heuristic and the obtained results have been reported in the diagram with the aim of detecting the Pareto-front of the proposed heuristics. As the reader can notice in Fig. 4, H1, H2 and H4 represent the Pareto-front of the non-dominated heuristics and, as a consequence, H3 and H5 could be ignored by any potential APMS analyst. As widely discussed in the previous sections, H4 is the best heuristic method in terms of costs for solving the kinds of APMS problem described in the proposed DOEs. H1 is a little bit more computationally expensive but should assure a higher residual life at the end of the planning horizon. H2 is the most computationally expensive strategy among the non-dominated ones but it is capable of keeping very high the residual life of the pavement at the sixth year, thus enabling a cost saving in the next M&R planning session, after 6 years. Therefore, H2 could be preferred over the alternative M&R policies when the airport maintenance staff want to adopt a farsighted strategy that potentially would reduce the M&R costs in the subsequent 6-years planning time window.

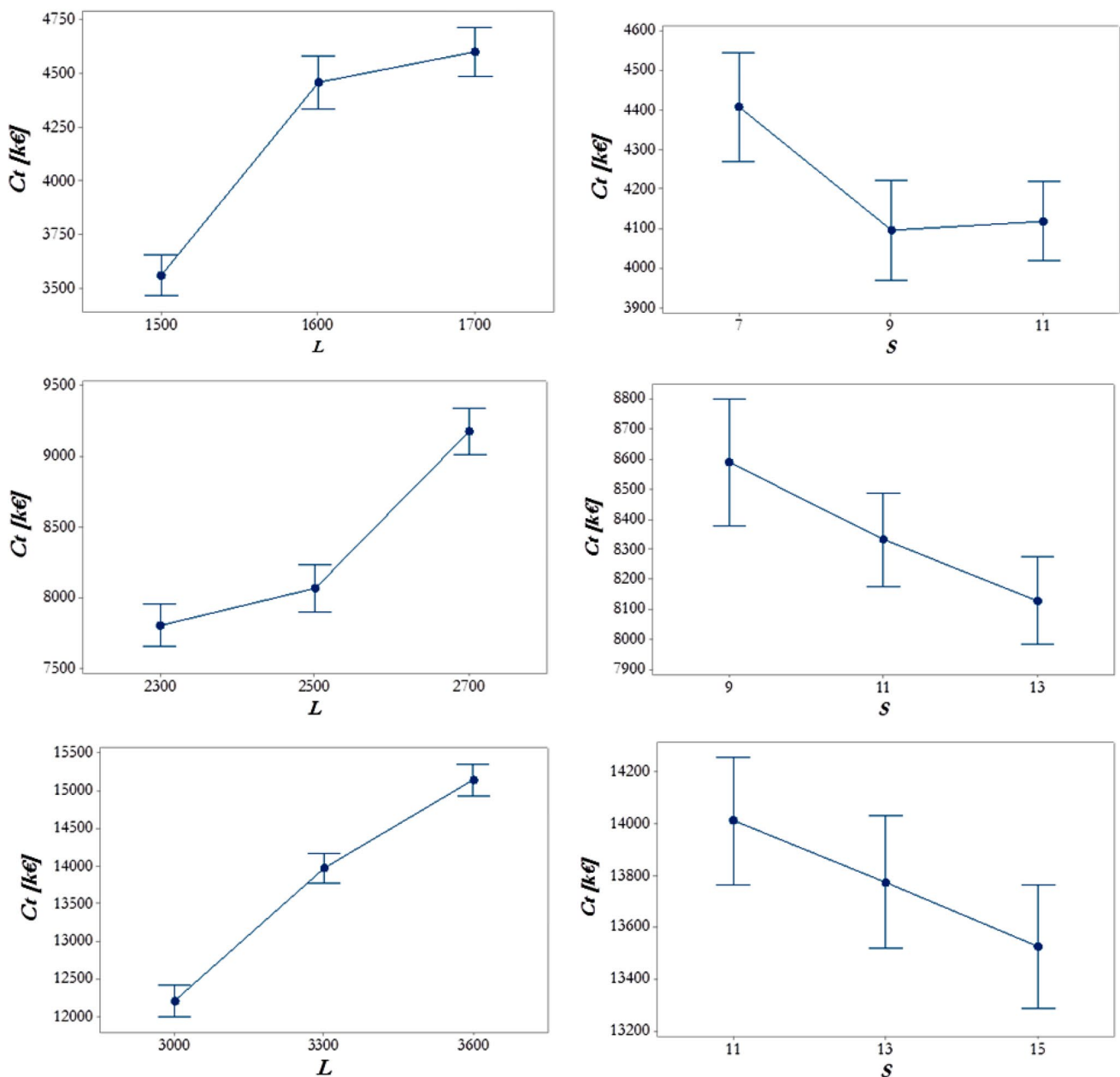


Fig. 5 Relations between runway length (L)—total costs (C_t) and number of sections (s)—total costs (C_t). Interval plots at 95% confidence level: $WL=30$ (top plots), $WL=45$ (middle plots), $WL=60$ (bottom plots)

5.3 Sensitivity Analysis

As H_4 has been detected as the most effective heuristic in reducing the total cost of maintenance, it has been used to carry out a sensitivity analysis on the main factors of the proposed design of experiments, namely, the length of the runway L and the number of sections S . To this end, a series of interval plots at 95% of confidence levels, assuming the total cost as response variable, have been arranged.

Figure 5 reports the interval plots for each DOE (i.e., WL) at varying the runway length L and the number of sections

S . As expected, the total cost of maintenance is significantly influenced by the runway length, despite the different width levels. Particularly, when the runway width is low ($WL=30$), there is not any statistical difference in terms of total maintenance cost if the runway length is equal to 1600 or 1700 m. Of course, the cost is remarkably lower when the length is equal to 1500 m. Conversely, when the runway width is equal to the medium level ($WL=45$), a statistical irrelevance in terms of total cost emerges for runways long 2300 and 2500 m, while runways long 2700 m are more costly under a statistical viewpoint. Interestingly, when the runway width is

very high ($WL=60$), the statistical significance of the length factor on the total cost is confirmed at each level. As far the number of sections is concerned, without loss of generality we can say that the total cost of maintenance decreases as S increases. However, it is worth noting that, for each runway width value, the medium level of S is statistically irrelevant as the corresponding interval plot always interferes with the lower- and upper-level plots. Nevertheless, considering that the number of sections of a branch, i.e., the runway, depends purely on the conditions of the pavement in terms of package composition, course thicknesses, traffic, etc., it could be useful to assess the relationship between the number of sections and the maintenance costs.

6 Managerial Implications

The objective of the proposed research consists of providing effective decision-making tools for managing maintenance activities of airport pavement systems focusing on the runway infrastructure. The initial assumption is to consider the maintenance plan by considering both practical and economical point of views. Specifically, this paper illustrates different M&R optimization strategies (see Table 2), because it is believed that there is not a single optimal strategy, while several efficient solutions can be taken into consideration by any airport manager when searching for the best compromise between duration and operative impact of the maintenance intervention on the runway. In fact, the more incisive the maintenance action in terms of pavement quality restoring the more invasive in terms of disruption of the regular airport operations. On the other hand, there are alternative activities providing a lower impact in terms of quality restoring but requiring a short time (i.e., a few hours) to be accomplished: thus, they can be preferable when any disruption on the airport operations is needed. In this context, the proposed heuristic algorithms provide a series of valid alternatives to airport managers, who can assess in a short time the best M&R strategy in terms of cost/operativity ratio. Moreover, the distinction between planning period (T) and control period (T_c) may be configured as another adding-value in terms of managerial implication. In fact, the spread $T_c - T$ can be considered as a time leg useful to calibrate the impact of the maintenance interventions executed at the end of the planning time. A greater time leg means that the airport manager aims at assuring a higher quality level of the pavement at the end of the planning time. Conversely, a smaller time leg would be preferable when the minimization of maintenance costs is a primary objective along with a higher operativity of the airport, at the price of providing frequent low-quality maintenance actions at the end of T .

7 Conclusions

In this paper, the pavement maintenance management problem in airport field is addressed.

The leading contribution of the proposed approach relies on the implementation of five new heuristic algorithms, each one based on a different managerial rationale. Regardless of the strategy used, the study also exploits a modified K-means machine learning method to gather sample units having similar pavement deterioration conditions into homogeneous pavement portions in terms of three distinct quality metrics (RL, IRI, PCI). Besides, the identification of specific groups of pavement portions characterized by poor pavement quality conditions, i.e., the critical work-zones, allowed to reduce the complexity of the optimization problem at hand. The ability and the robustness of each heuristic in solving the proposed APMS constrained optimization problem is evaluated by investigating a large number of randomly generated flexible runways having a sufficient level of diversity, in accordance with ICAO Annex 14. The obtained numerical results revealed that no single method can be selected as the most performing one if both the cost and the quality conditions of the pavements are simultaneously considered as performance objectives. In fact, a Pareto-front analysis taking into account the total cost and Residual Life, shows that H1, H2 and H4 represent the non-dominated heuristics. H4 is the most profitable heuristic method for solving the kinds of APMS problem described in the proposed study. H1 is a little bit more computationally expensive but should assure a higher residual life at the end of the planning horizon. H2 is the most computationally expensive strategy among the non-dominated ones but it is capable of keeping very high the residual life of the pavement at the end of the planning time, likely enabling further cost saving in the next M&R planning session. Finally, a sensitivity analysis by means of H4 has been carried out. It demonstrates that the total cost of maintenance is significantly influenced by the runway length, despite the different width levels. On the other hand, though the number of sections is a less influencing, it emerges that the total cost of maintenance decreases as S increases.

Due to the exploratory nature of this work, several actions can be pursued for future research. For sure, a real-world case study is desirable to test the efficacy of the proposed M&R planning methods. Furthermore, other aspects concerning the profit loss or the negative social impact deriving from the runway close for maintenance could be considered as objectives to be minimized in future multi-objective studies. Finally, another research perspective would be carried out using different decay curves incorporating pavement deterioration uncertainty into pavement management optimization.

Appendix

Pseudo-code: Heuristic 1

Step 1 Initialization: $\forall w = 1, \dots, W; P_w^q(t), \forall t = 1, \dots, T_c, w = 1, \dots, W, q = 1, \dots, Q | Q = 3; Th_q, q = 1, \dots, Q; T, T_c; x = [0]^{W \times T};$

Step 2: Identification of t_w^{min} :
For each work-zone $w=1, \dots, W$ and at each time $t=1, \dots, T$ find the earliest time t_w^{min} at which one of the performance measures is lower than the critical threshold Th_q :

$$t_w^{min} = \min_{t=1, \dots, T} t | P_w^q(t) \leq Th_q, \forall q = 1, \dots, Q$$
End

Step 3: Selection of the most suitable activity \tilde{x} to be executed at time t_w^{min} .
 3.1 **For** each work-zone $w=1, \dots, W$ compute the current constraint violation $viol$.
 3.2 **For** each type of maintenance intervention $i = 1, \dots, N$, use SDA to test the effect of such activity on the performance measures of that work-zone $P_w^q(t)$.
If there exist activities capable of eliminating any constraint violation ($viol=0$), select the less costly one (\tilde{x}):
 $x_{w,t_w^{min}} = \tilde{x}$; Go to Step 3.1.
End
If no type of M&R activity is able to set at zero the constraint violation, select the one capable of minimizing such violation, at minimum cost (\tilde{x}): $x_{w,t_w^{min}} = \tilde{x}$; Go to Step 3.1.
End
End

Step 4: Objective function computation.
Step 5: Stop algorithm.

Pseudo-code: Heuristic 2

Step 1: Initialization: $\forall w = 1, \dots, W; P_w^q(t), \forall t = 1, \dots, T_c, w = 1, \dots, W, q = 1, \dots, Q | Q = 3; Th_q, q = 1, \dots, Q; T, T_c; X^{H1}, X^{H2};$

Step 2: Generate solution x^1 from H1.

Step 3: Identify the set Γ of the time periods in which type-1 and type-2 M&R activities occur.

Step 4: Set t_{min} :

$$t_{min} = \min_{t \in \Gamma} t;$$

Step 5: Updating solution X^{H1} :
For each critical work-zone $w = 1, \dots, W$
For each time period $t=1, \dots, T$
If $t_w^{min} = t_{min}$ do nothing;
Else, similarly to Step 2 of H1, search for the less costly M&R activity \tilde{x} to be executed at time t_{min} capable of assuring no constraint violation for that work-zone until T_c . Set $X_{w,t}^{H2} = \tilde{x}$.
End
End
End

Step 6 Objective function computation.
Step 7: Stop algorithm.

Pseudo-code: Heuristic 3

Step 1: Initialization: $\forall w = 1, \dots, W; P_w^q(t), \forall t = 1, \dots, T_c, w = 1, \dots, W, q = 1, \dots, Q | Q = 3; Th_q, q = 1, \dots, Q; T, T_c; X^{H1}, X^{H2};$

Step 2: Generate solution x^1 from H1.

Step 3: Identify the set Ω of the time periods in which all types of M&R activities occur, with exception of type-0 “do-nothing” actions.

Step 4: Set t_{freq} as the time period at which M&R activities have the highest frequency of occurrence.

Step 5: Updating solution X^{H1}
For each critical work-zone $w = 1, \dots, W$
For each time period $t=1, \dots, T$
If $t_w^{min} = t_{freq}$ do nothing;
Elseif $t_w^{min} > t_{freq}$ then similarly to Step 2 of H1, search for the less costly M&R activity \tilde{x} to be executed at time t_{freq} capable of assuring no constraint violation for that work-zone until T_c . Set $X_{w,t}^{H3} = \tilde{x}$.
Elseif $t_w^{min} < t_{freq}$ then search for the less costly M&R activity \tilde{x} to be executed at time t_w^{min} capable of assuring no constraint violation for that work-zone at least until t_{freq} . Update solution $X_{w,t}^{H3} = [\tilde{x}, X_{w,t}^{H3}]$.
End
End
End

Step 6: Objective function computation.
Step 7: Stop algorithm.

Pseudo-code: Heuristic 4

Step 1 Initialization: $\forall w = 1, \dots, W; P_w^q(t), \forall t = 1, \dots, T_c, w = 1, \dots, W, q = 1, \dots, Q | Q = 3; Th_q, q = 1, \dots, Q; T, T_c; x = [0]^{W \times T};$

Step 2: Identification of t_w^{min} :
For each work-zone $w=1, \dots, W$ and at each time $t=1, \dots, T$ find the earliest time t_w^{min} at which one of the performance measures is lower than the critical threshold Th_q :

$$t_w^{min} = \min_{t=1, \dots, T} t | P_w^q(t) \leq Th_q, \forall q = 1, \dots, Q$$
End

Step 3: Selection of the most suitable activity \tilde{x} to be executed at time t_w^{min} :
 3.1 **For** each work-zone $w=1, \dots, W$ compute the current constraint violation $viol$.
 $flag=0$;
 3.2 **For** each type of maintenance intervention $i = 1, \dots, N$, use SDA to test the effect of such activity on the performance measures of that work-zone $P_w^q(t)$.
If there exist any activities capable of eliminating any constraint violation ($viol=0$), select \tilde{y} as the one successive to the less costly one (\tilde{x}):
If $flag=1$ **then**
 $x_{w, t_w^{min}} = \tilde{y}$;
 $flag=flag+1$;
 Go to Step 3.2.
Else
 Go to Step 3.1
End
End
If no type of M&R activity is able to set at zero the constraint violation, select the one capable of minimizing such violation, at minimum cost (\tilde{x}): $x_{w, t_w^{min}} = \tilde{x}$; Go to Step 3.1.
End
End
End

Step 5: Objective function computation.
Step 4: Stop algorithm.

Pseudo-code: Heuristic 5

Step 1 Initialization: $\forall w = 1, \dots, W; P_w^q(t), \forall t = 1, \dots, T_c, w = 1, \dots, W, q = 1, \dots, Q | Q = 3; Th_q, q = 1, \dots, Q; T, T_c; x = [0]^{W \times T};$

Step 2: Identification of t_w^{min} :
For each work-zone $w=1, \dots, W$ and for each time $t=1, \dots, T$ find the earliest time t_w^{min} at which one of the performance measures is lower than the critical threshold Th_q :

$$t_w^{min} = \min_{t=1, \dots, T} t | P_w^q(t) \leq Th_q, \forall q = 1, \dots, Q$$
End

Step 3: Selection of the most suitable activity $\tilde{x} \in \{3,4\}$ to be executed at time t_w^{min} :
 3.1 **For** each work-zone $w=1, \dots, W$
 3.2 **If** the constraint violation at time t_w^{min} is due to a structural problem (i.e., $P_w^{RL}(t_w^{min})=0$) then
 select $\tilde{x} = 3$;
 $x_{w, t_w^{min}} = \tilde{x}$;
 Apply the M&R activity at time t_w^{min} and use SDA to search another constraint violation
If any violation exists then
 update t_w^{min} ;
 Go to Step 3.2
Else
 Go to Step 3.1
End
Else
 $\tilde{x} = 4$;
 $x_{w, t_w^{min}} = \tilde{x}$;
 Apply the M&R activity at time t_w^{min} and use SDA to search another constraint violation
If any violation exists then
 update t_w^{min} ;
 Go to Step 3.1
Else
 Go to Step 3.2
End
End
End
End

Step 4: Objective function computation.
Step 5: Stop algorithm.

Funding Open access funding provided by Università degli Studi di Catania within the CRUI-CARE Agreement.

Data Availability The basic codes of this work are available from the corresponding author on request.

Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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