Incorporating Pavement Deterioration Uncertainty into Pavement Management Optimization

Pavement management systems can be used to efficiently allocate limited maintenance budgets to better align with pavement deterioration. However, pavement deterioration is subject to uncertain factors that complicate the prediction of future pavement conditions accurately, entailing differences in the optimum maintenance strategy. This paper addresses this challenge by introducing a method to aid local engineers in optimizing the scheduling of maintenance activities under uncertain pavement deterioration conditions. Markov chains are used to simulate the variability of life-cycle performance. Moreover, a multi-objective optimization of an urban network is carried out to find the maintenance program that minimizes the mean life-cycle cost, maximizes the mean user benefit, and minimizes the standard deviation of life-cycle cost. This third objective enables the optimization routine to minimize the possibility of unintentionally increasing the life-cycle cost due to system variability. This approach results in a reduction of the life-cycle cost variability by up to 62%, provides pavement strategies that benefit road users as a result of better pavement conditions, and reduces the risk of resorting to costly future maintenance activities.

Keywords: pavement deterioration; optimization; pavement management; uncertainty; performance

Word count: 6771

Introduction

Considerable research has been published during the last three decades in the area of pavement management (Abaza *et al.* 2004). This research is motivated by both budget limitations and the demands of increasingly higher quality, comfort, and safety from road users (Meneses and Ferreira 2015). Pavement management systems (PMS) are used to efficiently allocate limited budgets (Zhang *et al.* 2012) and support the pavement management decision-making process (Fuentes *et al.* 2019). At a network-level, pavement management systems support the development of policies that optimize resources and ensure that maintenance strategies over each pavement segment will benefit the entire pavement network (Wu and Flintsch 2009, Sathaye and Madanat 2011).

To support good decision-making, a PMS requires an accurate and efficient pavement deterioration prediction model (Butt *et al.* 1987, Yang *et al.* 2005, Hassan *et al.* 2017). Abaza et al. (2004) also concluded that, in addition to the prediction model, an optimization process is needed as a basic component of a PMS to guarantee the best possible pavement conditions. Thus, prediction models forecast future pavement conditions, allowing for the design of optimal maintenance strategies during the service life, and thereby reducing life-cycle costs (Dong *et al.* 2015). Although both components must be integrated to devise a set of optimal maintenance strategies according to future conditions, efforts have been focused, separately, on the formulation of either a complete optimization tool (Zhang *et al.* 2012, Meneses and Ferreira 2015, Torres-Machi *et al.* 2017, Santos *et al.* 2019) or on modeling deterioration through advanced probabilistic approaches (Hassan *et al.* 2017, Moreira *et al.* 2018, Park and Kim 2019).

In other infrastructure applications, researchers have applied probabilistic performance approaches in multi-objective optimization (Morcous and Lounis 2005, Jha and Abdullah 2006, Wu and Flintsch 2009). Morcous and Lounis (2005) presented a new methodology, combining Markov-chain models and heuristic algorithms, to obtain the percentages of bridge deck areas that require maintenance every year of an analysis period. Jha and Abdullah (2006) proposed a similar methodology for optimizing the maintenance of roadside structures. Regarding pavement maintenance, Wu and Flintsch (2009) obtained optimal global strategies for maintaining a pavement network, such as the annual budget allocation and the fraction of the network that must be maintained each year. In these studies, Markov chains are used to predict the fractions of the total network that are in each state of deterioration, translating the stochastic model into a deterministic result. However, Markov models can also be used to predict the probability of a road segment being in a certain condition at a particular time in the future (Ortiz-García et al. 2006, Hassan et al. 2017). These models can be combined with Monte Carlo simulation to obtain a wide range of possible performance scenarios (Osorio-Lird et al. 2018), and therefore, the variability of deterioration. Although Markov models have been used to obtain global strategies (Morcous and Lounis 2005, Jha and Abdullah 2006, Wu and Flintsch 2009), and develop pavement performance models (Hassan et al. 2017, Osorio-Lird et al. 2018), these have not been implemented together within a multi-objective optimization framework to schedule pavement network maintenance activities considering the probabilistic distribution of future performance. Such an approach allows pavement agencies to define maintenance activities with a high degree of likelihood and reduce unplanned costs.

Building on this approach, this paper goes one step further by proposing a method that uses Markov chains and Monte Carlo simulation in the multi-objective optimization of the mean life-cycle cost, the mean benefit, and the standard deviation of the life-cycle cost. Using this approach, rather than obtaining global strategies, the optimization tool can use the prediction of pavement conditions to specify the road segments that should be maintained each year, considering the different treatments that can be applied while taking into account their corresponding uncertainty. In addition, the inclusion of the standard deviation of the life-cycle cost as an optimization objective allows the optimization routine to consider the risk of a pavement section deteriorating at high rate and, consequently, the possibility that such a different deterioration rate can cause a change in strategy. Therefore, this paper proposes a method to optimize pavement maintenance at both project and network level under the uncertainty of future pavement deterioration. The method is tested in a case study of an urban network consisting of 15 flexible road sections.

Literature review

Markov models

Deterioration is characterized by its uncertain nature, as it can vary under variable traffic load and environmental conditions (de Melo e Silva *et al.* 2000, Yang *et al.* 2005, Park and Kim 2019). While deterministic models, such as regression techniques, evaluate the deterioration based on specific conditions (Butt *et al.* 1987, Meegoda and Gao 2014), probabilistic models consider the probability of occurrence of a range of possible outcomes due to the effect of varying factors affecting road performance (Ortiz-García *et al.* 2006). Within the subset of probabilistic models, many authors agree that Markov models can be effectively applied to pavement deterioration (Abaza *et al.* 2004, Yang *et al.* 2005, Wu and Flintsch 2009, Pérez-Acebo *et al.* 2018). Beginning in 1980, when the Arizona Department of Transportation in the United States introduced Markov processes into their pavement management system (Kulkarni *et al.* 1980), numerous studies have used this method to predict future pavement conditions (de Melo e Silva *et al.* 2000, Abaza *et al.* 2004, Wu and Flintsch 2009, Moreira *et al.* 2018). The Markov process assigns "transition probabilities" to each element in a set, which represent the probability of transitioning from one condition state to another during a given time period (Wu and Flintsch 2009). Using this technique, the future state is estimated solely on the current state of the element and the likelihood of transitioning from this current state. Osorio-Lird et al. (2018) found that these models can be developed without a large historical database. In addition, Morcous and Lounis (2005) pointed out that these models are functional for large-sized networks, and can capture randomness that ultimately affects the network performance.

Pavement optimization

With regard to optimization, both economic and technical aspects (concerning the pavement performance) of the pavement system are the most commonly adopted objectives. For example, Wu and Flintsch (2009) proposed a multi-objective optimization considering both the maintenance cost and the network level of service as objective functions. This second technical objective was evaluated as the weighted average state condition of the pavement. Other authors have used the long-term effectiveness of maintenance strategies as a technical objective, as measured in terms of service life extension, the average condition improvement, or the area bounded by the post-treatment performance curve, the do-nothing performance curve, and upper or lower threshold (Dong and Huang 2012, Chen et al. 2017). Li et al. (2007) sought to maximize the total effectiveness-to-cost ratio of the network, with effectiveness calculated as the area between the predicted pavement performance curve and the minimum acceptable level multiplied by length and traffic volume of the road segment. Dong et al (2015) also used cost-effectiveness to compare different maintenance actions at different years in the future.

While all approaches include agency costs as part of life-cycle cost optimization of pavement networks, user costs are not always included since they are difficult to evaluate precisely and impartially, while also tending to dominate the decision process when considered (Golabi and Pereira 2003, Wang *et al.* 2003, Wu and Flintsch 2009). While some authors included environmental and social aspects in the analysis (Zhang *et al.* 2010, Torres-Machi *et al.* 2017), others have suggested that a technical evaluation based on effectiveness indirectly considers social aspects, since larger effectiveness can be translated into increased societal benefit due to the improved condition of the pavement (Torres-Machi *et al.* 2015).

Method

The method proposed for the multi-objective optimization of a pavement network is presented in Figure 1. It is comprised of two steps: (1) pavement performance models and (2) life-cycle optimization. The first step develops a pavement performance models based on data that is collected from in-service pavement sections. The Pavement Condition Index (ASTM, 2018) is calculated based on pavement distress observations of different pavement sections over an inspection period. Based on the changing distress observations over time, a Markov transition matrix is created, evaluating the probability of a pavement section transitioning from one state of distress or deterioration to another in one-year period. Finally, a set of performance curves are obtained through Monte Carlo simulation that varies future conditions that affect pavement deterioration.

[Figure 1 near here]

The second step is life-cycle optimization, which includes the definition of optimization objectives, the definition of a set of maintenance action options and their effects on pavement condition, the multi-objective optimization routine, and the interpretation of results. Different objectives are adopted to evaluate each maintenance program and select the best solution. Recognizing that some maintenance actions are only viable for certain levels of pavement distress (i.e., minor maintenance has little effect on high deteriorated pavements), treatment options are presented depending on the condition of the pavement when the maintenance is applied. If the variability of deterioration covers more than one pavement state, different treatments are applied with a corresponding probability. The objectives and the treatments are considered in the multi-objective optimization to obtain the optimal maintenance program that minimizes or maximizes the objectives, while ensuring compliance with optimization constraints. Finally, the results of the multi-objective optimization at the project-level and network-level are interpreted in order to draw conclusions regarding the advantages or disadvantages of delaying maintenance, the likelihood of increasing the life-cycle cost due to variability of future deterioration, and the optimal maintenance strategy.

Performance models

Data collection

Observations of pavement conditions over time are required to define and calibrate the pavement performance models. This study uses observations from the Long Term Pavement Performance (LTPP) program database (https://infopave.fhwa.dot.gov/). This database was developed by the Federal Highway Administration of the United States. Several studies (Khattak and Alrashidi 2013, Chen *et al.* 2017, Moreira *et al.* 2018) have used this dataset to analyze the performance of pavement over extended time periods. This database collects information on pavement sections located in the United States and Canada for use by engineers and researchers. The dataset contains information related to the structure, climate, traffic, and performance of pavement sections. In addition to data on pavement performance, climate data is downloaded as part of this study, as several authors have shown that pavement deterioration depends on climate factors, particularly the temperature and the average annual precipitation (Perera and Kohn 2001, Hall *et al.* 2003, Anastasopoulos and Mannering 2015). LTPP database information on pavement distress is used to calculate the Pavement Condition Index (PCI). The PCI is a surrogate measure of the structural integrity and surface operational condition of the pavement (ASTM 2018). This index is calculated as a function of the severity and extent of 19 types of pavement distresses, providing a value between 0 and 100. PCI can be divided into different rating scales (Table 1) according to the pavement state (PS) (ASTM 2018). This paper uses the first five PS ratings to classify the pavement condition. Thus, pavements with PCI lower than 40 are all considered as "very poor."

[Table 1 near here]

Markov chain creation

Markov chains are used as a modeling method for evaluating the deterioration of the pavement over time. Markov prediction modeling is a stochastic process that evaluates the expected probability of a pavement section to be in a certain state that will deteriorate to another state over a period of time based on available data or expert judgement (Yang *et al.* 2005). This method is characterized by predicting the future event from the present event, independent of past events. The Transition Probability Matrix (TPM) is comprised of the conditional probabilities of a pavement segment to transition from any one deterioration state to another (Pérez-Acebo *et al.* 2018). Thus, even though pavement deterioration is continuous over time, a finite number of fixed condition bands are defined and the condition of pavement segments are analyzed at specific points in time (Osorio-Lird *et al.* 2018).

Equations 1 and 2 show the matrix, $P^{t,t+1}$, whose elements, $p_{ij}^{t,t+1}$, represent the probability to move from state *i* to *j* from time *t* to *t+1*. The diagonal elements represent the probability that there is no transition of state from time *t* to *t+1*. The lower left elements below the principle diagonal are zero when no maintenance is applied, while the upper right elements represent the probability to deteriorate by one or more condition states within a time increment from time *t* to *t+1*.

$$P^{t,t+1} = \begin{bmatrix} p_{11}^{t,t+1} & \cdots & p_{1n}^{t,t+1} \\ \vdots & \ddots & \vdots \\ p_{n1}^{t,t+1} & \cdots & p_{nm}^{t,t+1} \end{bmatrix};\ p_{ij}^{t,t+1} \geq 0\ (i,j = 1,2,\ldots,n);\ \sum_{j=1}^{n} p_{ij}^{t,t+1} = 1\ (i = 1,2,\ldots,n) \qquad (1)$$

$$p_{ij}^{t,t+1} = Pr\left[X(t+1) = j \middle| \middle| X(t) = i\right] \qquad (2)$$

The TPM is constructed based on available data or expert knowledge. Transition probability matrices created from available data need information of the evolution of pavement conditions over time. When intervals between inspections are not constant for all pavement sections, a continuous time Markov process can be adopted (Moreira *et al.* 2018). In this case, authors such as Park and Kim (2019) and Surendrakumar et al. (2013) have used Poisson's method to obtain the transition matrix for one year. The Poisson distribution (Equation 3) provides the probability that there will be $j - i$ events over a time interval of length *t*.

$$\mathrm{p}_{ij}(t) = \frac{(\lambda t)^{j-i}}{(j-i)!} e^{-\lambda t} \qquad (3)$$

where λ is obtained from the LTPP database as the number of elements per time interval that move from a state *i* to *j* over the time *t*.

Monte Carlo simulation

Once the TPM is defined, the predicted life-cycle performance is calculate using Monte Carlo simulation (Osorio-Lird *et al.* 2018). The Monte Carlo simulation builds a set of performance curves that model the condition of the pavement as a function of time. Each curve begins with the pavement being in a “good” state and remaining in the same state or transitioning to another state at every timestep, depending on the randomness of the simulation. To build this Monte Carlo simulation, a Cumulative Probability Matrix (CPM) is obtained for each transition probability. Next, random numbers are generated and compared to the cumulative probability matrix to determine the evolution of the states of each pavement segment over the analysis period. Then, the pavement condition (PC) is set at 5 at the initial time to show a decreasing deterioration model. In this way, the pavement condition has an inverse relationship to the pavement state, which means the following correspondences: PS1 (5≤PC<4), PS2 (4≤PC<3), PS3 (3≤PC<2), PS4 (2≤PC<1) and PS5 (PC=1). The minimum pavement condition is PC = 1, as pavements in very poor condition cannot deteriorate to another state. Finally, to obtain the final performance curve, the waiting times in each condition range are linearized through the slope of the deterioration trend, which can be obtained as $-1/(n+1)$, where n is the number of time periods within a range (Osorio-Lird *et al.* 2018). This process is repeated 10,000 times to obtain 10,000 possible performance curves.

Life-cycle optimization

Objectives definition

While pavement performance models are used to predict future performance, different objectives or criteria are required to evaluate the consequences of each maintenance program and, therefore, select the optimal overall maintenance program. The objectives should be set to align with the final goals of the decision-maker. This paper aims to find a method to optimize pavement maintenance in a network while considering the uncertainty of future pavement deterioration rates. For this purpose, although environmental and social aspects are important, they are not explicitly considered in accordance with the final goal. The life-cycle cost variability is considered and represents the deviation from the predicted cost due to the need to perform a different maintenance treatment as a result of unknown future conditions. Penadés-Plà et al. (2020) considered the standard deviation and the coefficient of variation of life-cycle cost to obtain robust solutions.

This paper proposes the standard deviation of the life-cycle cost (LCC) as an objective to find robust solutions with low sensitivity to the variation of the deterioration rate. In addition to the standard deviation of LCC, the mean LCC and the mean user benefit (B) are also objectives. The LCC sums the cost of maintenance activities throughout the analysis period taking into account the time-value of money by time-discounting all future cash flows (Kleiner 2002) using a discount rate. The mean LCC is calculated as the mean value of the network life-cycle cost for all deterioration curves. The user benefit is estimated as the area between the predicted pavement performance curve and the minimum acceptable level multiplied by traffic volume of the road segment. The user benefit objective represents the improvement in pavement condition that benefits the motoring public (Haider and Dwaikat 2011). While this study proposes three objectives for optimization, other objectives that are based on environmental and social impacts could also be considered following the same method. Thus, the objectives considered in this paper are the mean life-cycle cost (LCC_m) (Equation 4), the mean benefit (B_m) (Equation 5), and the standard deviation of the life-cycle cost (LCC_{sd}) (Equation 6).

$$LCC_m = mean \sum_{i=1}^{Ns} LCC_{ij} \quad (4)$$

$$B_m = mean \sum_{i=1}^{Ns} B_{ij} \quad (5)$$

$$LCC_{sd} = std \sum_{i=1}^{Ns} LCC_{ij} \tag{6}$$

$$LCC_{ij} = \sum_{k=1}^{Nt} \frac{Cost_{kij}}{(1+\upsilon)^{t_k}} * A_i \tag{7}$$

$$B_{ij} = \int_{t=0}^{T} (PC_{ij}(t) - PC_{min})\, dt * AADT_i \tag{8}$$

where LCC_{iJ} is the life-cycle cost of a pavement section *i* for a deterioration curve *j*; N_s is the number of sections; N_t is the number of maintenance actions incurred over the analysis period; *v* is the discount rate; $cost_{kij}$ is the cost per unit area of each maintenance action *k* of a pavement section *i* for a deterioration curve *j*; A_i is the area of a pavement section *i*; t_k is the year of the action *k*; B_{ij} is the benefit of a pavement section *i* for a deterioration curve *j*; PC_{min} is the minimum pavement condition considered and $AADT_i$ is the average annual daily traffic of a pavement section *i*. A discount rate of 2% is assumed (Dong *et al.* 2013, García-Segura *et al.* 2017a).

Maintenance action options

Maintenance actions are performed to restore or rehabilitate the pavement condition. When maintenance is conducted, the pavement segment is assumed to return to PS1 ("good condition"). The type of maintenance performed depends on the state of the pavement. This paper considers three maintenance action options: minor maintenance, major maintenance, and rehabilitation. These maintenance actions are based on a literature review (Wu and Flintsch 2009, Zhang et al. 2012, Meneses and Ferreira 2015). In further studies, these reference maintenance actions can be extended. Table 2 summarizes the cost of each action (ITEC 2020). Minor maintenance can be applied for pavements with condition PS1 and is comprised of routine maintenance in the form of crack sealing, pothole patching and localized surface treatment. Major maintenance consists of an asphalt overlay (up to 10 cm) used on road segments with a condition of PS2. Finally, rehabilitation is comprised of surface milling and structural resurfacing that restores the pavement condition to PS1 for pavements with a condition of PS3, PS4 or PS5. The selected maintenance action depends on the condition of the pavement when maintenance is programmed. If the variability of deterioration covers different pavement states, different treatments are applied with a corresponding probability.

[Table 2 near here]

Multi-objective optimization

The optimization problem is formulated as the minimization of LCC_m (Equation 9), maximization of B_m (Equation 10), and minimization of LCC_{sd} (Equation 11). One optimization constraint is imposed as a minimum condition threshold for the entire network over the analysis period. In this case, the median value of pavement condition must be greater than 1. This means that half of the pavement conditions must be greater than 1, considering all the deterioration possibilities and all years of the analysis period (Equation 12). The variables of the optimization problem are the time of the first maintenance application (t_1) and the time interval between the following applications (Δt) of all the network sections. The aim of the multi-objective optimization is to find the values of the variables that maximize or minimize the objectives.

$$\min LCC_m(x) \quad (9)$$

$$\max B_m(x) \quad (10)$$

$$\min LCC_{sd}(x) \quad (11)$$

$$g(x) = \text{median } PC_{ij}(t) > 1 \quad (12)$$

Figure 2 shows a flowchart of the optimization process. The multi-objective optimization uses the Multiobjective Harmony Search algorithm, which was used in other multi-objective optimizations providing satisfactory results (García-Segura and Yepes

2016, García-Segura et al. 2017b, Sierra et al. 2018). Firstly, the algorithm parameters are assigned: the Harmony Memory Size (HMS) or number of solutions, the Harmony Memory Considering Rate (HMCR), and the Pitch Adjusting Rate (PAR). These two last parameters (HMCR and PAR) define the creation of new solutions. The process starts with a population of HMS feasible random solutions. To evaluate the feasibility and fitness of solutions, the simulation of the performance curves and the assessment of the objective functions and constraints are carried out. Feasible solutions are saved in the Harmony Memory (HM). The improvisation of new solutions is based on the combination of three approaches: random selection, memory consideration and pitch adjustment of memory. The first approach diversifies the search by exploring all possible values. The second approach selects values from the HM. Finally, the third approach selects from solutions stored in the HM and introduces slight variations. The probability of choosing the first approach is 1 minus HMCR. Otherwise, the new alternative is obtained from the HM with a probability of HMCR. In this case, the probability of choosing the second approach is 1 minus PAR, while the probability of choosing the third one is PAR.

New feasible solutions are created following this strategy and, afterward, are compared to the solutions in memory based on Pareto criterion. Each iteration creates HMS new solutions and updates the Harmony Memory and Pareto solutions. As multi-objective optimization is governed by several conflicting objective functions, Pareto criterion is used to select the non-dominated solutions, which are the solutions that cannot be improved without worsening the value of any one objective. This set represents the best maintenance programs, from which a specific solution can be selected by a decision maker. This study uses the hypervolume measure as a termination criterion (García-Segura et al. 2017b, García-Segura et al. 2018). This indicator evaluates the convergence towards the ideal point, as well as the representative distribution of solutions along the front. A complete flowchart of the algorithm can be found in García-Segura and Yepes (2016).

[Figure 2 near here]

Result interpretation

Project or segment level

The method proposed at project or segment level provides the optimal maintenance program for a pavement section according to the established objectives. This first step provides insight regarding the advantages or disadvantages of a delayed maintenance action. This information contributes to understanding the likelihood of increasing the life-cycle cost due to the variability of future deterioration rates. In this case, a multi-objective optimization is carried out to minimize LCC_m and maximize B_m. The maximum and minimum life-cycle cost is also given for each Pareto solution. Note that the pavement area and the average annual daily traffic are not considered at this level, as this analysis is performed at project level. Pareto solutions represent the best maintenance programs which have the highest user benefit and the lowest life-cycle cost.

Network level

At the network level, Pareto solutions are obtained for the LCC_m, B_m and LCC_{sd} objectives. Therefore, results show the best and robust maintenance schedules of the entire network that have low sensitivity to the variation of the deterioration rate, reduce the life-cycle cost, and increase user benefit. This approach provides a set of optimal solutions so that pavement managers can select the most appropriate solution according to their preferences. For example, the closest solution to the ideal point can be selected as the most satisfactory solution (Wu and Flintsch 2009, Penadés-Plà *et al.* 2020). In addition, conclusions about the relationship between the objectives can be drawn, highlighting the tradeoff between LCC_m and LCC_{sd} when a benefit improvement is sought.

Case study

This research proposes a case study of an urban network of 15 asphalt pavement sections located in a wet-no freeze (WNF) climatic region. The Latin hypercube sampling (LHS) technique is employed to design a case study that covers all pavement characteristics. This technique constructs a sample of variable values guaranteeing that all of the design variables are represented covering their respective ranges (Penadés-Plà *et al.* 2019). The variables that correspond to the road characteristics are initial pavement state, area (m^2), and annual average daily traffic (AADT). This method determines 15 non-overlapping intervals for each variable and assigns one point in each region so that each point corresponds to a combination of different intervals of each design variable. Table 3 shows the characteristics of the 15 pavement sections used for the case study. The maximum value allowed for the three variables are an initial state of PS4, an area of 2,000 m^2, and an AADT equivalent to 60,000 vehicles per day. The multi-objective optimization aims to determine the best maintenance program over an analysis period of 25 years.

[Table 3 near here]

Performance models

Observation data of flexible pavements located in urban road sections were downloaded from the LTPP database. For this case study, sections located in WNF climatic regions were filtered. Consequently, information of pavement distresses was obtained for a total of 51 sections inspected over a period of between 2 and 18 years. From the distress observations, the PCI was calculated as a measure of the condition of the pavement. The

Transition Probability Matrix (TPM) for one-year period was calculated from the data following Equations 1-3 (Equation 13). In this case, P_{11}=0.87 corresponds to the probability of no transition ($j=i$) occurring in one year when the initial state *i* is 1, while P_{12}=0.12 corresponds to the probability of a transition to state 2 (j-i=1) occurring in one year when the initial state *i* is 1.

$$TPM = \begin{bmatrix} 0.87 & 0.12 & 0.01 & 0.00 & 0.00 \\ 0.00 & 0.83 & 0.16 & 0.01 & 0.00 \\ 0.00 & 0.00 & 0.68 & 0.26 & 0.06 \\ 0.00 & 0.00 & 0.00 & 0.75 & 0.25 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix} \quad (13)$$

The Cumulative Probability Matrix (CPM) is calculated by adding up the probabilities of the row until the *j* position (Equation 14). To model the evolution of the condition states during the analysis period, random numbers are compared to the CPM. The row is selected according to the current state. The column whose number is greater than the random number shows the state after the cycle. For example, if the current state is 1 and the random number is 0.5, the first row is selected and 0.5 is compared against 0.87. As 0.87 is greater than 0.5, the future state will be 1. Whereas, if the current state is 1 and the random number is 0.9, the future state will be 2. The process is repeated for all the years to provide the evolution of the states during the analysis period. Then, PC, which represents an inverse correspondence to PS, is evaluated and the waiting times in each condition range are linearized. Figure 3 shows that after 5 years the mean pavement condition is 3.8, while the 5th percentile is 2 and the 95th percentile is 4.8.

$$CPM = \begin{bmatrix} 0.87 & 0.99 & 1.00 & 1.00 & 1.00 \\ 0.00 & 0.83 & 0.99 & 1.00 & 1.00 \\ 0.00 & 0.00 & 0.68 & 0.94 & 1.00 \\ 0.00 & 0.00 & 0.00 & 0.75 & 1.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix} \quad (14)$$

[Figure 3 near here]

Life-cycle optimization

A calibration process of the optimization routine suggested the algorithm parameters: HMS = 200, HMCR = 0.8, PAR = 0.4. The optimization process finished after ten consecutive HM improvisations with a difference in hypervolume value of less than 0.0005. In this case, 15 iterations and 760 iterations are performed for the project and network level, respectively.

Project or segment level

The set of Pareto solutions are shown in Figure 4, which represent the best maintenance programs that exhibit the highest user benefit and the lowest life-cycle cost. Note that dash lines divide different values of the time interval between applications. As explained previously, the pavement area and the average annual daily traffic are not considered due to the fact that this analysis is performed at the project level. The five points with the greatest mean life-cycle cost (around 150€/m^2) have a Δt of 1 year, while t_1 varies between 1 year and 5 years. These solutions have higher mean life-cycle cost because a maintenance action is performed every year, but they have no possibility of needing a costly treatment. The following three solutions have a Δt of 2 years. These solutions have a lower mean life-cycle cost (around 95€/m^2), but they have a higher likelihood of ultimately having a greater maximum life-cycle cost (around 210€/m^2). Although the variability of each maintenance action after two years is not high, the sum of the actions over the 25 years leads to a greater maximum life-cycle cost.

[Figure 4 near here]

The solutions with the lowest life-cycle cost are those with a Δt of 17 years, with a benefit of approximately 65. These solutions have an 11% likelihood of needing minor maintenance, a 16% likelihood of needing major maintenance, and a 73% likelihood of needing rehabilitation. Note that a strategy of no maintenance during the 25 years has a benefit of 43.7, although this solution is not feasible as it violates the optimization constraint. Thus, when maintenance is delayed, LCC_m and B_m are reduced. Although the maintenance actions are more expensive, the sum of the maintenance costs in the analysis period is lower. Regarding B_m, a delayed maintenance application deteriorates the pavement and results in a negative impact on the user benefit. The maximum life-cycle cost increases initially as the risk of needing a more expensive maintenance action increases, but then decreases because the number of interventions in the analysis period is lower.

Network level

The network case study proposed consists of an urban network of 15 asphalt pavement sections that covers characteristics of initial condition state, area and AADT. Figure 5 presents the two-dimensional projections of the non-dominated Pareto frontiers for the three-objective optimization problem. Figure 6 shows the three-dimensional projection of the non-dominated Pareto surface for the three-objective optimization problem. Figure 5a shows an asymptotic relationship between LCC_m and B_m, such that a large increase of B_m is realized for small marginal increases of LCC_m at the lowest values of LCC_m. At increasingly larger LCC_m values, a smaller marginal benefit increment is observed with an increase in LCC_m. For instance, increasing the mean life-cycle cost from $1\cdot10^6$ € to $1.5\cdot10^6$€, results in a user benefit increase of 22%. However, from this point, a larger increase of the mean life-cycle cost from $1.5\cdot10^6$ € to $3\cdot10^6$ € is needed to increase the user benefit by only 11%. In addition, lower variability was observed as both LCC_m and B_m increase. These solutions point the decision-maker toward more frequent maintenance schedules. When maintenance is applied at short intervals, the mean life-cycle cost is higher, but the mean benefit is also higher and the variability of life-cycle cost is lower. This outcome is in line with the results at the project level.

[Figure 5 near here]

The closest solution to the ideal point is marked in Figures 5a and 5b. In this solution, LCC_m is $1.54 \cdot 10^6$ €, B_m is $3.26 \cdot 10^7$, and LCC_{sd} is $2.73 \cdot 10^5$ €. This satisfactory solution is located around the aforementioned point, from which a benefit improvement is more expensive. In addition, this solution has a reduced standard deviation of the life-cycle cost. Analyzing its maintenance schedule, it is worth mentioning that pavement sections with smaller area and higher AADT are prioritized. Particularly, this solution presents the time between the applications (Δt) shown in Table 4. Pavement sections with an area smaller than 660 m^2 are maintained every year, as they have smaller LCC_m and LCC_{sd}. If they have an area between 660 m^2 and 1,320 m^2, they are also maintained every year, except for low volume roads, which are maintained every 15-17 years as there are a small number of users that can benefit of the good condition of the pavement. Finally, high volume roads with area greater than 1,320 m^2 are maintained every 5 years, while low volume roads are maintained every 15-17 years. Regarding medium volume cases, both results are obtained, suggesting a Δt of 15-17 years in very large sections. This last case corresponds to large sections with medium volume, whose maintenance is expensive and confers little benefit.

[Table 4 near here]

Note that this case study covers all possible cases, although some are less likely. The first maintenance application depends on the initial condition state. If t_1 of Pareto solutions is analyzed, roads with an initial condition state of PS1 undergo a first maintenance action before 17 years, while roads with an initial condition state of PS2, PS3 or PS4, undergo a first maintenance action before 11, 5 and 3 years, respectively. This limitation is conditioned by the constraint imposed in the multi-objective optimization.

Regarding maintenance actions, these are applied with a corresponding probability depending on the time interval. For instance, solutions which have a time interval of 5 years have a 58% likelihood of needing minor maintenance, a 26% likelihood of needing major maintenance, and a 16% likelihood of needing rehabilitation. Alternatively, if a time interval of 15 years is chosen, minor maintenance is needed with a likelihood of 14%, major maintenance with a likelihood of 21%, and rehabilitation with a likelihood of 65%. Thus, when the standard deviation of the life-cycle cost is optimized, the preferred annual maintenance schedules reduce the variability of the deterioration and the possibility of requiring costly future maintenance. These solutions also present good user benefit results. However, these solutions also tend to have higher mean life-cycle cost due to the high number of maintenance events during the analysis period.

An alternative solution to reduce the standard deviation of the life-cycle cost is carrying out maintenance with a Δt of 15-17 years. In this case, rehabilitation would be needed with a high likelihood. Each maintenance action is more expensive, but the sum of the maintenance costs in the analysis period is lower. This also results in the user benefit objective being reduced significantly. Therefore, the proposed satisfactory solution combines different time intervals to obtain balanced results for the three objective functions.

Validation

To verify the benefits of this method, a bi-objective optimization was carried out without considering the variability of future pavement deterioration and the results of both approaches were compared. The mean value of the pavement condition was considered for the pavement deterioration and the bi-objective optimization was performed for the objectives LCC_m and B_m. Although the results provided a 2D Pareto front, the LCC_{sd} was calculated for the set of solutions as in the previous sections. These solutions are represented on the multi-objective view of the three-objective optimization (Figure 6) to compare these findings against the variability of the solution when pavement deterioration is ignored. Solutions resulting from the bi-objective optimization have higher variability in the life-cycle cost. It is worth noting that for a value of LCC_m around $2.3 \cdot 10^6$, the bi-objective optimization obtains a solution (LCC_m, B_m, LCC_{sd}) of ($2.3 \cdot 10^6$, $3.5 \cdot 10^7$, $10.9 \cdot 10^5$), while the three-objective optimization obtains a solution of ($2.3 \cdot 10^6$, $3.5 \cdot 10^7$, $4.1 \cdot 10^5$). Therefore, the method proposed in this paper achieves a reduction of the life-cycle cost variability of 62%. This reduction indicates that the LCC_{sd} objective is important to consider when searching for robust solutions that present low variability of life-cycle cost.

[Figure 6 near here]

Conclusions

This paper proposes a method to optimize pavement maintenance at both project and network levels while considering the uncertainty of future pavement deterioration rates. Pavement performance models are obtained using the Markov chain method and Monte Carlo simulations. The variability of the deterioration process is explicitly considered in the optimal design of pavement maintenance programs. A multi-objective optimization minimizes the mean life-cycle cost, maximizes the mean benefit, and minimizes the standard deviation of the life-cycle cost. The optimization routine aims to find low cost and robust pavement maintenance programs that have low sensitivity to the variation of the pavement deterioration rate and that benefit the motoring public by ensuring good pavement conditions over the analysis period.

Results of the multi-objective optimization at the project-level reveal that delayed maintenance actions reduce the LCC_m and B_m. The maximum life-cycle cost increases initially as the likelihood of needing a more expensive maintenance action increases. With additional delay, the maximum life-cycle cost then decreases because the number of interventions in the analysis period is lower. As far as network is concerned, the results reflect an asymptotic relationship between LCC_m and B_m, highlighting a point beyond which a benefit improvement is marginally more expensive. The closest solution to the ideal point is located at this point. The optimal strategy corresponds to frequent maintenance actions being taken on high volume pavement segments, leading to a higher user benefit, combined with a reduction of life-cycle cost by delaying maintenance in road sections with greater area and lower AADT. To validate the benefits of this method, a bi-objective optimization was carried out without considering the variability of pavement deterioration. Findings indicate that the proposed method achieves a reduction of life-cycle cost variability by up to 62%, reducing the likelihood of requiring a costly future maintenance action.

Recommendations

Pavement agencies, departments of transportation, and road directorates that manage large-scale pavement networks can scale this proposed method to consider a large number of pavement sections. Further, pavement managers can develop their own management strategies based on a case study that covers all network characteristics and use it in support of efficient decision-making and the identification of robust maintenance schedules. Some agencies may also include environmental and social aspects affected by the pavement maintenance strategy. For instance, life-cycle CO_2-equivalent emissions can be considered using Equation 7. In this case, the emissions per unit area of each maintenance action would be considered instead of the cost per unit area and the discount rate would be altered.

Limitations and further research

The proposed method was tested on a case study of an urban network consisting of 15 flexible road sections located in a wet-no freeze climatic region. Therefore, the results are limited to this case study and further research is needed to apply the method to other case studies with varying climate zones, types of pavement, and traffic conditions. Regarding the deterioration models, this study does not consider different Markov transition matrices for roads with different traffic conditions. Such an improvement would allow for a more accurate assessment of the pavement deterioration and an improved prioritization of road sections. Finally, the identification and consideration of a larger dataset of historical pavement distress observations should be undertaken, which may result in the construction of different Markov chains that can be used to develop more accurate post-treatment pavement performance models.

References

Abaza, K.A., Ashur, S.A., and Al-Khatib, I.A., 2004. Integrated pavement management system with a Markovian prediction model. *Journal of Transportation Engineering*, 130 (1), 24–33.

Anastasopoulos, P.C. and Mannering, F.L., 2015. Analysis of pavement overlay and replacement performance using random parameters hazard-based duration models. *Journal of Infrastructure Systems*, 21 (1).

ASTM, 2018. *Standard practice for roads and parking lots pavement condition index surveys (No. ASTM D6433-18)*. West Conshohocken: American Society for Testing and

Materials.

Butt, A.A., Shahin, M.Y., Feighan, K.J., and Carpenter, S.H., 1987. *Pavement performance prediction model using the Markov process*. Transportation Research Record 1123. Washington, D.C.: Transportation Research Board.

Chen, X., Zhu, H., Dong, Q., and Huang, B., 2017. Optimal thresholds for pavement preventive maintenance treatments using LTPP data. *Journal of Transportation Engineering, Part A: Systems*, 143 (6), 04017018.

Dong, Q. and Huang, B., 2012. Evaluation of effectiveness and cost-effectiveness of asphalt pavement rehabilitations utilizing LTPP data. *Journal of Transportation Engineering*, 138 (6), 681–689.

Dong, Q., Huang, B., and Richards, S.H., 2015. Calibration and Application of Treatment Performance Models in a Pavement Management System in Tennessee. *Journal of Transportation Engineering*, 141 (2), 4014076.

Dong, Y., Frangopol, D.M., and Saydam, D., 2013. Time-variant sustainability assessment of seismically vulnerable bridges subjected to multiple hazards. *Earthquake Engineering & Structural Dynamics*, 42 (10), 1451–1467.

Fuentes, L., Camargo, R., Arellana, J., and Velosa, C., 2019. Modelling pavement serviceability of urban roads using deterministic and probabilistic approaches probabilistic approaches. *International Journal of Pavement Engineering*, 1–10.

García-Segura, T., Penadés-Plà, V., and Yepes, V., 2018. Sustainable bridge design by metamodel-assisted multi-objective optimization and decision-making under uncertainty. *Journal of Cleaner Production*, 202, 904–915.

García-Segura, T. and Yepes, V., 2016. Multiobjective optimization of post-tensioned concrete box-girder road bridges considering cost, CO2 emissions, and safety. *Engineering Structures*, 125, 325–336.

García-Segura, T., Yepes, V., Frangopol, D.M., and Yang, D.Y., 2017a. Lifetime reliability-based optimization of post-tensioned box-girder bridges. *Engineering Structures*, 145, 381–391.

García-Segura, T., Yepes, V., and Frangopol, D.M., 2017b. Multi-objective design of post-tensioned concrete road bridges using artificial neural networks. *Structural and Multidisciplinary Optimization*, 56 (1), 139–150.

Golabi, K. and Pereira, P., 2003. Innovative pavement management and planning system for road network of Portugal. *Journal of Infrastructure Systems*, 9 (2), 75–80.

Haider, S.W. and Dwaikat, M.B., 2011. *Estimating optimum timing for preventive maintenance treatment to mitigate pavement roughness*. Transportation Research Record 2235. Washington, D.C.: Transportation Research Board.

Hall, K.T., Correa, C.E., and Simpson, A.L., 2003. *Performance of flexible pavement maintenance treatments in the long-term pavement performance SPS-3 experiment*. Transportation Research Record 1823. Washington, D.C.: Transportation Research Board.

Hassan, R., Lin, O., and Thananjeyan, A., 2017. A comparison between three approaches for modelling deterioration of five pavement surfaces. *International Journal of Pavement Engineering*, 18 (1), 26–35.

ITEC, 2020. Catalonia Institute of Construction Technology. BEDEC PR/PCT ITEC material database.

Jha, M.K. and Abdullah, J., 2006. A Markovian approach for optimizing highway life-cycle with genetic algorithms by considering maintenance of roadside appurtenances. *Metal Finishing*, 104 (6), 404–419.

Khattak, M.J. and Alrashidi, M., 2013. Performance of preventive maintenance treatments of flexible pavements. *International Journal of Pavement Research and*

Technology, 6 (3), 184–196.

Kleiner, Y., 2002. Scheduling inspection and renewal of large infrastructure assets. *Journal of Infrastructure Systems*, 7 (4), 136–143.

Kulkarni, R., Golabi, K., Finn, F., and Alviti, E., 1980. *Development of a network optimization system*. San Francisco, California: The Woodward-Clyde Consultants.

Li, N., Haas, R., and Huot, M., 2007. *Integer programming of maintenance and rehabilitation treatments for pavement networks*. Transportation Research Record 1629. Washington, D.C.: Transportation Research Board.

Meegoda, J.N. and Gao, S., 2014. Roughness progression model for asphalt pavements. *Journal of Transportation Engineering*, 140 (8), 4014037.

de Melo e Silva, F., Van Dam, T.J., Bulleit, W.M., and Ylitalo, R., 2000. *Proposed Pavement Performance Models for Local Government Agencies in Michigan*. Transportation Research Record 1699. Washington, D.C.: Transportation Research Board.

Meneses, S. and Ferreira, A., 2015. Flexible pavement maintenance programming considering the minimisation of maintenance and rehabilitation costs and the maximisation of the residual value of pavements. *International Journal of Pavement Engineering*, 16 (7), 571–586.

Morcous, G. and Lounis, Z., 2005. Maintenance optimization of infrastructure networks using genetic algorithms. *Automation in Construction*, 14 (1), 129–142.

Moreira, A. V, Tinoco, J., Oliveira, J.R.M., and Santos, A., 2018. An application of Markov chains to predict the evolution of performance indicators based on pavement historical data. *International Journal of Pavement Engineering*, 19 (10), 937–948.

Ortiz-García, J.J., Costello, S.B., and Snaith, M.S., 2006. Derivation of transition probability matrices for pavement deterioration modeling. *Journal of Transportation*

Engineering, 132 (2), 141–161.

Osorio-Lird, A., Chamorro, A., Videla, C., Tighe, S., and Torres-Machi, C., 2018. Application of Markov chains and Monte Carlo simulations for developing pavement performance models for urban network management. *Structure and Infrastructure Engineering*, 14 (9), 1169–1181.

Park, S.H. and Kim, J.H., 2019. Comparative analysis of performance prediction models for flexible pavements. *Journal of Transportation Engineering, Part B: Pavements*, 145 (1), 04018062.

Penadés-Plà, V., García-Segura, T., and Yepes, V., 2019. Accelerated optimization method for low-embodied energy concrete box-girder bridge design. *Engineering Structures*, 179, 556–565.

Penadés-Plà, V., Yepes, V., and García-Segura, T., 2020. Robust decision-making design for sustainable pedestrian concrete bridges. *Engineering Structures*, 209, 109968.

Perera, R.W. and Kohn, S.D., 2001. *LTPP data analysis: Factors affecting pavement smoothness*. Transportation Research Board. Washington, D.C.: National Cooperative Highway Research Program Project 20-50.

Pérez-Acebo, H., Bejan, S., and Gonzalo-Orden, H., 2018. Transition probability matrices for flexible pavement deterioration models with half-year cycle time. *International Journal of Civil Engineering*, 16 (9), 1045–1056.

Santos, J., Bressi, S., Cerezo, V., and Lo Presti, D., 2019. SUP&R DSS: A sustainability-based decision support system for road pavements. *Journal of Cleaner Production*, 206, 524–540.

Sathaye, N. and Madanat, S., 2011. A bottom-up solution for the multi-facility optimal pavement resurfacing problem. *Transportation Research Part B: Methodological*, 45

(7), 1004–1017.

Sierra, L.A., Yepes, V., García-Segura, T., and Pellicer, E., 2018. Bayesian network method for decision-making about the social sustainability of infrastructure projects. *Journal of Cleaner Production*, 176, 521–534.

Surendrakumar, K., Prashant, N., and Mayuresh, P., 2013. Application of Markovian probabilistic process to develop a decision support system for pavement maintenance management. *International Journal of Scientific & Technology Research*, 2 (8), 295–303.

Torres-Machi, C., Chamorro, A., Pellicer, E., Yepes, V., and Videla, C., 2015. Sustainable pavement management: Integrating economic, technical, and environmental aspects in decision making. *Transportation Research Record: Journal of the Transportation Research Board*, 2523, 56–63.

Torres-Machi, C., Pellicer, E., Yepes, V., and Chamorro, A., 2017. Towards a sustainable optimization of pavement maintenance programs under budgetary restrictions. *Journal of Cleaner Production*, 148, 90–102.

Wang, F., Zhang, Z., and Machemehl, R.B., 2003. Decision-making problem for managing pavement maintenance and rehabilitation projects. *Transportation Research Record 1853*, 1853 (1), 21–28.

Wu, Z. and Flintsch, G.W., 2009. Pavement preservation optimization considering multiple objectives and budget variability. *Journal of Transportation Engineering*, 135 (5), 305–315.

Yang, J., Gunaratne, M., Lu, J.J., and Dietrich, B., 2005. Use of recurrent Markov chains for modeling the crack performance of flexible pavements. *Journal of Transportation Engineering*, 131 (11), 861–872.

Zhang, H., Keoleian, G.A., and Lepech, M.D., 2012. Network-level pavement asset management system integrated with life-cycle analysis and life-cycle optimization. *Journal of Infrastructure Systems*, 19 (1), 99–107.

Zhang, H., Keoleian, G.A., Lepech, M.D., and Kendall, A., 2010. Life-cycle optimization of pavement overlay systems. *Journal of Infrastructure Systems*, 16 (4), 310–322.

Table 1. Pavement states and descriptions (ASTM 2018)

Pavement state	Verbal description	PCI
PS1	Good	[100; 85)
PS2	Satisfactory	[85; 70)
PS3	Fair	[70; 55)
PS4	Poor	[55; 40)
PS5	Very Poor	[40; 25)
PS6	Serious	[25; 10)
PS7	Failed	[10; 0]

Table 2. Cost of pavement maintenance actions

Type of treatment	**Cost (€/m^2)**
Minor maintenance	8.18
Major maintenance	22.30
Rehabilitation	62.44

Table 3. Characteristics of the case study pavement network

	Initial pavement state	Area (m^2)	AADT (vehicles per day)
Road 1	PS1	902.4	43337.0
Road 2	PS3	1500.1	3295.6
Road 3	PS1	1631.8	20417.4
Road 4	PS4	446.4	27610.6
Road 5	PS1	1495.7	31722.0
Road 6	PS4	870.2	545.3
Road 7	PS3	1441.5	5218.6
Road 8	PS1	1978.7	32862.6
Road 9	PS1	1812.3	41985.9
Road 10	PS2	1583.6	8187.8
Road 11	PS2	635.0	53024.3
Road 12	PS3	506.1	45699.1
Road 13	PS1	1145.7	39487.4
Road 14	PS4	605.2	17228.0
Road 15	PS2	1755.9	3864.8

Table 4. Time between maintenance actions for the most satisfactory solution

		AADT		
		Low volume <19800 vpd	Medium volume [19800; 39600] vpd	High volume >39600 vpd
Area	Small <660 m^2	1	1	1
	Medium-sized [660; 1,320] m^2	15-17	1	1
	Big >1,320 m^2	15-17	15-17 / 5	5

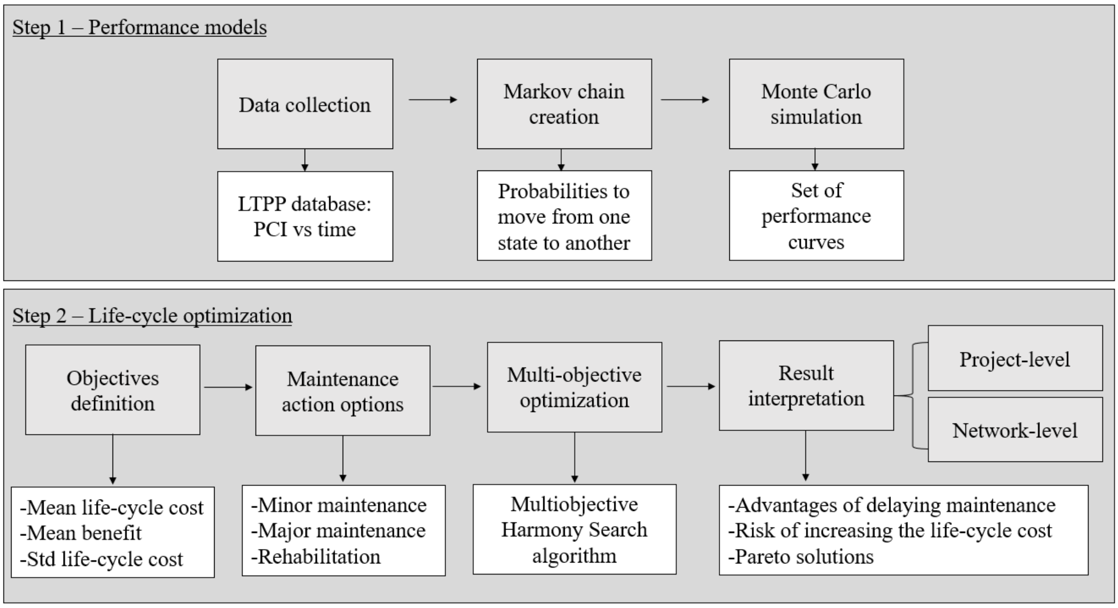


Figure 1. Schematic representation of the two-step pavement management system optimization; (top) Step 1 – performance models and (bottom) Step 2 – Life-cycle optimization

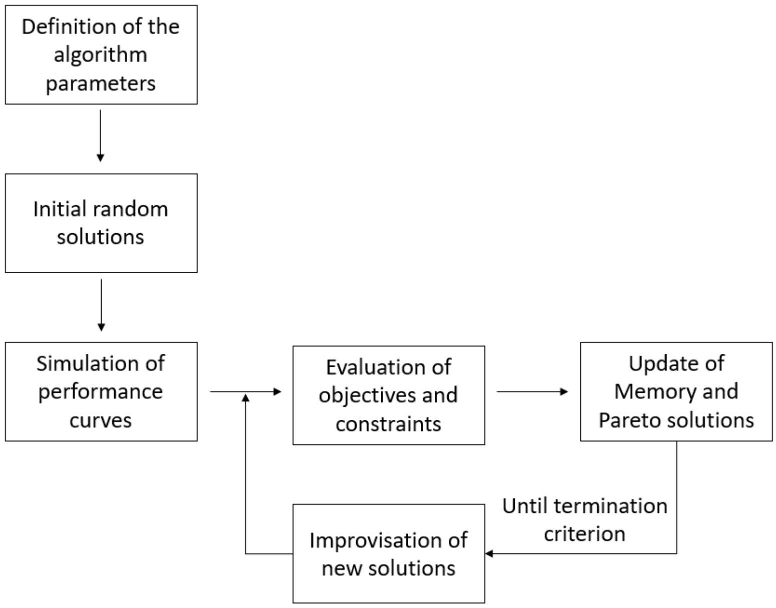


Figure 2. Flowchart of the optimization process

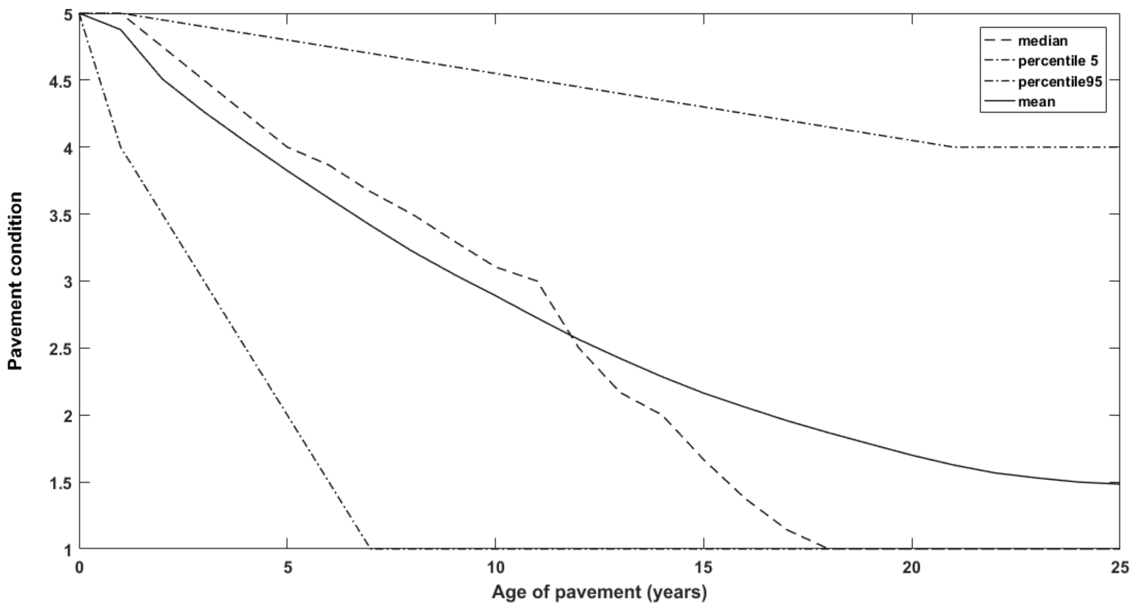


Figure 3. Expected pavement condition as a function of pavement age

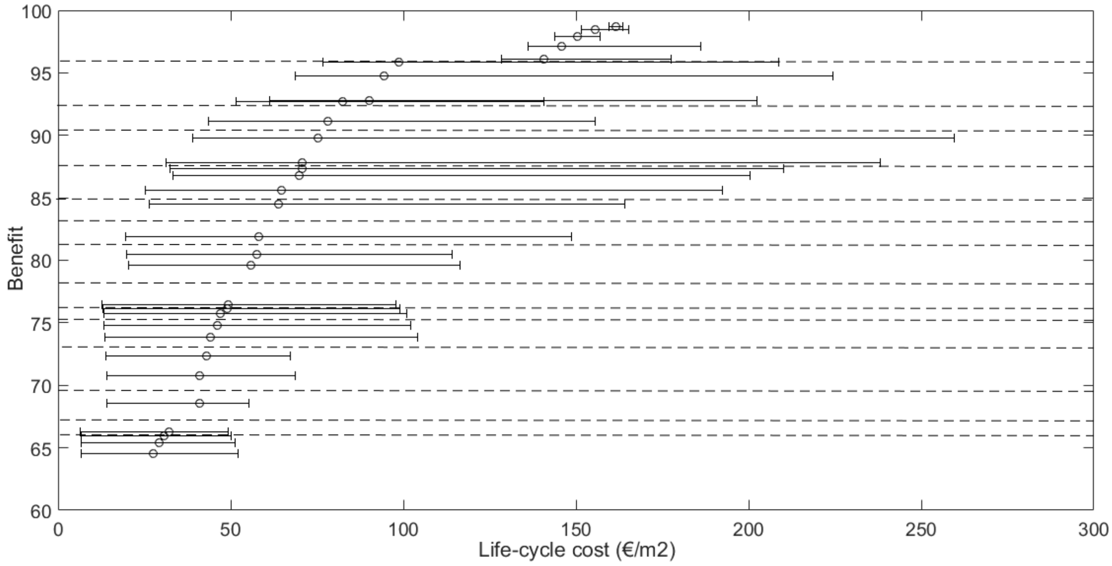
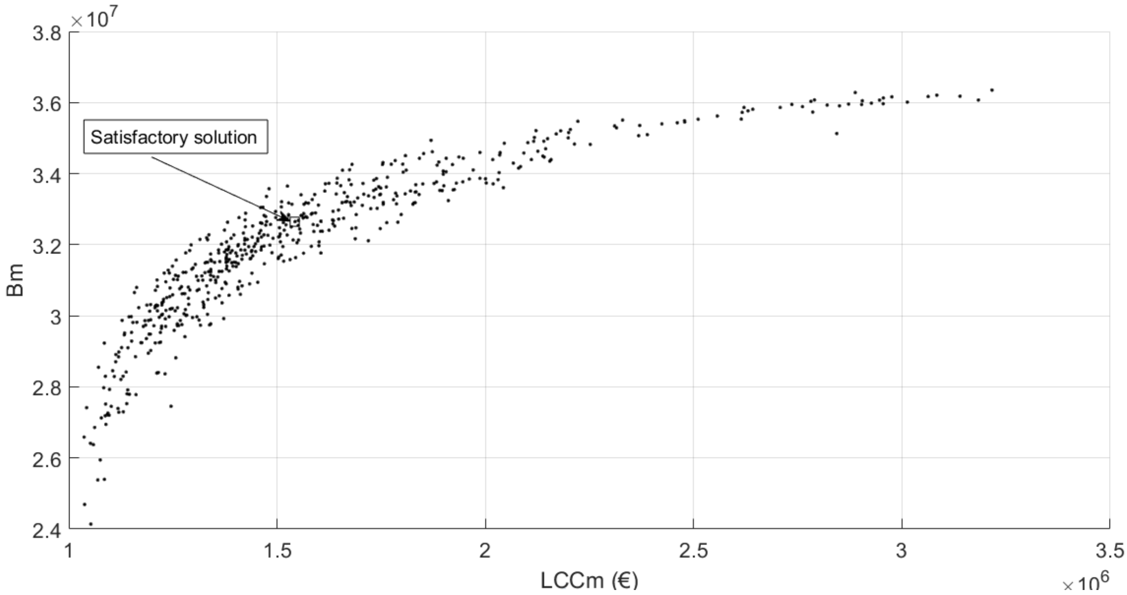
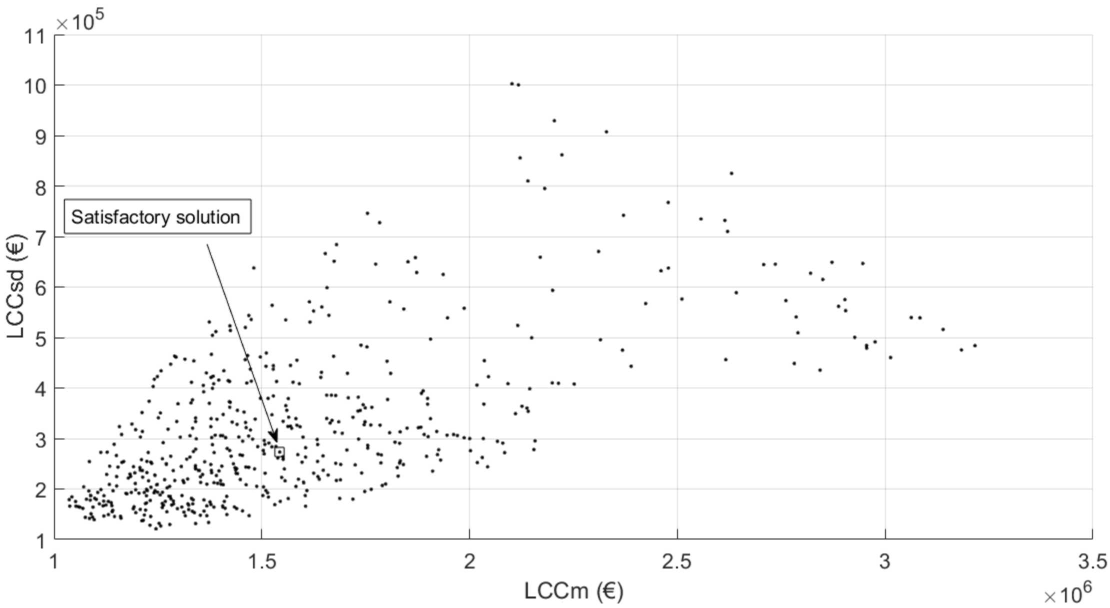


Figure 4. Pareto set of pavement management solutions at the project or segment level



(a) LCC_m versus B_m



(b) LCC_m versus LCC_{sd}

Figure 5. Network level Pareto front for (a) LCC_m versus B_m and (b) LCC_m versus LCC_{sd}

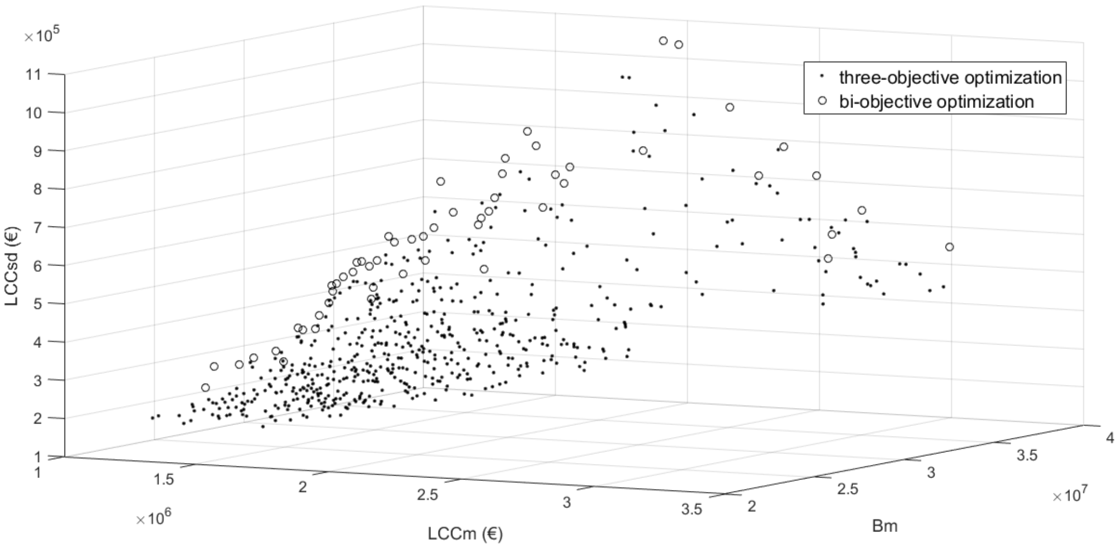


Figure 6. Multi-objective Pareto front characterizing LCC_m versus B_m versus LCC_{sd}

Figure captions

Figure 1. Schematic representation of the two-step pavement management system optimization; (top) Step 1 – performance models and (bottom) Step 2 – Life-cycle optimization

Figure 2. Flowchart of the optimization process

Figure 3. Expected pavement condition as a function of pavement age

Figure 4. Pareto set of pavement management solutions at the project or segment level

Figure 5. Network level Pareto front for (a) LCCm versus Bm and (b) LCCm versus LCCsd

Figure 6. Multi-objective Pareto front characterizing LCCm versus Bm versus LCCsd