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Optimal condition-based maintenance of asphalt-concrete pavement systems

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ABSTRACT
Maintenance is a necessary to keep assets, in this case, a pavement system, in good condition. Spending too much on maintenance is not efficient, while not spending enough may cause the condition to drop below a desired level. Therefore, in this paper, a conceptual approach, based on systems and control theory, is developed to improve the efficiency of maintenance of a pavement system, compared to the currently used maintenance approach where often only fixed bounds of the condition determine whether or not a maintenance action is required. A state-space description of the condition of the pavement system is chosen for predicting the future evolution of the health condition. This allows the use of a moving-horizon optimisation approach, to determine optimal anticipative maintenance actions. Furthermore, in this approach, the maintenance cost and the condition of the pavement system are optimised. This model-based approach can be applied in practice as well-documented data, from which degradation models can be constructed, are often available. In this paper, we also show how degradation models from the literature can be converted for use in the proposed condition-based maintenance approach. Note that because of the general character of the proposed maintenance optimisation approach, the degradation model and the chosen optimisation method that are used as illustration in this paper can easily be replaced by another one, depending on the needs of the user. A case study is performed, where a representative situation is considered using the developed approach and the maintenance approach currently used in practice. This case study shows how the approach works and what the cost reduction can be assuming that the models are accurate. The paper ends with a discussion and recommendations.

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Condition-based asset maintenance; predictive maintenance; model predictive control; time-instant-optimisation; asphalt-concrete pavements; degradation models

1. Introduction

A good road quality is important for the safe and efficient transport of people and goods and also for economic growth (Gertler et al., 2023; Ng et al., 2019; Wan et al., 2022).

Therefore, one of the goals of road authorities worldwide is to maintain high quality, and also improving maintenance efficiency, which contributes to a high road quality (Rijkswaterstaat, 2022).

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The current maintenance approach applied in practice is often proactive, where the decision to perform maintenance interventions is based on visual checks of the condition, which is acquired by inspections (Bandara & Gunaratne, 2001; Kim et al., 2016; Nautiyal & Sharma, 2021). Moreover, some road authorities use a well-developed decision model, while sometimes databases are used for their maintenance approach. For example, RWS (Rijkswaterstaat) in the Netherlands considers damages like cracks and ravelling, where the severity and extent are taken into account, while for other degradations only the severity is taken into account. The damages are transformed into classes with set boundaries, and rules to combine damages are used (Rijkswaterstaat, 1992).

As the cost for asset maintenance is very high, while decision methods are complex, much research has been done to improve the cost-efficiency of Maintenance and Rehabilitation (M&R).

One way to improve the cost-efficiency of M&R is using more effective maintenance treatments and methods. Some examples include: increasing the effectiveness of the applied maintenance method, for example, using thin overlays and chip sealing (Chen et al., 2002) or by applying appropriate preparations and methods for maintenance, such as adhesive intermediate layers, modified asphalts and aggregates that adhere better to the design specifications (Hai-Feng et al., 2015). In Pan et al. (2021), the effect of hot in-place recycling, milling and filling, thin hot mix asphalt and micro-surfacing on expressways in China are analysed with rutting depth as a performance indicator. In this case, it is found that hot in-place recycling results in the highest effectiveness in terms of cost.

Next to finding a proper maintenance treatment for improving the cost-efficiency of pavement M&R, finding the best moment to apply it is important, and this implies that prediction of the condition of the pavement system is essential. Using Machine Learning (ML) techniques on historical data obtained by inspections, maintenance alerts can be given and the best maintenance interventions can be determined and an extension of the lifecycle by 3–10 years can be achieved (Morales et al., 2021). It must be noted that predictions based on historic data have limitations, as input factors such as traffic loading and intensity can change, new pavement materials can be introduced, new maintenance methods can be adopted or regulations can change. Another important factor is climate change (Qiao et al., 2015).

The overall condition of pavement systems is often given as a single Performance Quality Index (PQI) that is based on the aggregation of several degradations, such as cracks, ride quality, rutting depth, friction, structural strength, etc. All these degradations can be given as performance condition indices and selecting an appropriate performance condition index is very important for determining the most effective maintenance option to reset the degradation (Khurshid et al., 2014).

The International Roughness Index (IRI) is most commonly employed worldwide to characterise longitudinal irregularities in road system management, serving as a measure of pavement performance and quality (Múčka, 2017). In Dotto Bueno et al. (2023), a prediction model for IRI based on the average calculated fatigue damage and empirical data is proposed, and in Soncim et al. (2018) a prediction model for IRI, based on expert knowledge and experience, is developed to be used for pavements where no historical data are available. Prediction models for the IRI, based on regression techniques, and on artificial network techniques, are developed in Abdelaziz et al. (2020), where the artificial network techniques resulted in more accuracy of the model. However, an accurate overall condition cannot always be found using performance indicators, as often the condition can only be explained by a combination of these (Morales et al., 2021). In case the PQI is based on more than one degradation, it is vital to select the appropriate weight of all of these degradations, which can be found by the entropy method (Gong et al., 2021).

Deterministic AASTHO (American Association of State Highway and Transportation Officials) models, such as prediction models for cracking, ravelling, potholes, patching, rutting, longitudinal roughness, skid resistance, traffic volume and climate are often used (Menesis & Ferreira, 2013, 2015). However, because these models are mainly applicable for roads in the USA, it can be shown that for other country models to suit pavement systems in those countries may work better than these AASTHO models (Jorge & Ferreira, 2012). So ideally we should have a good prediction model for all performance indices or even better: for every degradation and for the specific country where the M&R has to be optimised.

New methods, such as Artificial Intelligence (AI) and Machine Learning (ML), are often being used for prediction models (Kang et al., 2024) and they can lead to more efficient strategies for pavement M&R.

Optimising the time-scheduling of maintenance interventions and choosing the appropriate maintenance actions can be done with integer linear programming, when the degradation is given in tables (Correia et al., 2022). Evolutionary and swarm intelligence algorithms can be used for the optimisation of the maintenance schedule (Naseri et al., 2021), where it was found that the water cycle algorithm and ant colony optimisation were able to find the lowest maintenance costs. Genetic algorithms, which are based on natural selection and mutation mechanisms, yield very good results for scheduling problems (Lee, 2018), and these are used in many cases of pavement M&R optimisation (Hamdi et al., 2017; Jorge & Ferreira, 2012; Mathew & Isaac, 2014; Menesis & Ferreira, 2013, 2015; Naseri et al., 2021). Optimisation of maintenance strategies with genetic algorithms can also be combined with other approaches, for example, the prediction of the sideway force coefficient and accidents with artificial intelligence techniques (Bosurgi & Trifirò, 2005).

The limitations of the papers mentioned above are that only maintenance costs are considered and other costs are not included. With a multi-objective optimisation approach, it is possible to include other costs, such as agency costs (e.g. maintenance, provide reroutings) and residual costs where the pavement value depends on its current condition to provide a method to stimulate an optimal condition of the asset. Furthermore, sustainability and environmental concerns can be included in the determination of the effectiveness of maintenance strategies. Solutions can be found in using recycled materials, cold mixing methods but also reduction of the vehicle energy consumption (Liu et al., 2022).

Optimisation methods can also be applied to maintenance on railway tracks, an asset with similarities to pavements, so the literature in this field may be helpful. A multi-level optimisation approach for maintenance on rail tracks is developed in Su (2018) and Su et al. (2017), and this approach allows us to take strict bounds to the available time slots for performing maintenance into account, to deal with different time scales of degradation and maintenance interventions, to consider disruption of traffic and to increase tractability. The high-level, chance-constrained optimisation approach that is used, takes degradation models into account for the optimisation of maintenance. This chance-constrained approach may bring a less conservative optimum than a robust approach, as used in Su et al. (2019), as in the latter case, the distribution of stochastic signals is unknown and the worst-case scenario is chosen. Moreover, in Su (2018) and Su et al. (2017), a moving horizon optimisation approach is used, which has similarities with MPC (Rawlings & Mayne, 2013) and also a Time-Instant-Optimisation (TIO) approach is used, which is based on the work found in De Schutter and De Moor (1998). The high-level, chance-constrained optimisation approach in Su (2018) and Su et al. (2017) stands out because of its versatility, and it is a very good starting point for developing an optimisation approach of the maintenance of pavement systems.

No work has been found where the condition of the pavement system, which can consist of any number of sections, can be predicted from a degradation model, and single damages can be predicted and the effect of any M&R can be included and constraints to any variable can be set and where stochasticity, environmental effects, sustainability, recyclability, user costs, can be included in the optimisation and also good computational efficiency is obtained. All these issues will be addressed in the current paper.

2. Overall approach for model-based maintenance optimisation

The goal of this paper is to develop a conceptual approach to determine an optimal maintenance strategy, based on a predicted condition of the pavement, where the aim is to bring maintenance costs down while preserving the safe use of the pavement system. Furthermore, in the developed approach, it must be possible to set bounds to both maintenance costs and the condition of the pavement and also computational efficiency must be considered. Also, it must be possible to adapt the approach to large pavement systems with different pavement materials and constructions, where for different road sections, optimal maintenance strategies can be found. Moreover, it must be possible to choose the set of maintenance interventions and the effect of each of these interventions.

For pavement systems, historical data are often available and degradation models can be constructed (Ljung, 1998), which means that a model-based approach can be used. Moreover, for the Dutch pavement system, degradation models based on historical data are available (de Groot, 2002; Kuijper, 2014). Other degradation models can be adopted also, e.g. models that take future changes into account or models found with AI and ML (Brunton & Kutz, 2022).

The model-based approach for planning maintenance operations, as used in Su (2018) and Su et al. (2017), constitutes a good basis for this paper, for the following reasons: compared to other approaches, a less conservative optimum is obtained, less calculation effort is required, future states can be predicted and constraints can be used. Furthermore, in Su (2018) and Su et al. (2017) both the condition and the maintenance costs are optimised, so this approach makes it possible to ensure a minimum quality of the pavement system. Compared to railway networks, for pavement systems, the traffic disruption is less prominent as maintenance can be performed on one lane of a road, while traffic can still move on another lane at a slower pace. In the Netherlands, it is a common practice to maintain the right lane first, as it degrades faster because it is usually loaded more (more traffic and heavier loads). The cost of traffic disruption is more difficult to calculate than that of rail systems, as we have many unknown users. Moreover, the classification of the road condition is much more complex, and there are much more different maintenance options. For all these reasons, in the current paper, the railway maintenance optimisation method of Su (2018) and Su et al. (2017) is adapted and extended to *pavement* maintenance. From here, the method is developed step by step in the next sections. We start with a condition model, and next we show how the degradation model is adapted for MPC, and we add the effects of maintenance on the condition. Subsequently, a prediction model and the use of constraints and scaling are discussed. After this, the TIO optimisation approach is introduced, and it is shown how scenarios and chance-constraints can be used to minimise conservatism, caused by uncertainties.

As the resulting optimisation problem is non-linear and non-convex, it is not possible to compute an optimal strategy analytically, based on the prediction of the condition. Therefore, we use numerical optimisation approaches to find the optimal strategy. Finally, the approach, as developed in the current paper, is assessed in a case study, and the results are compared to the current maintenance approach and discussed.

The approach presented in the current paper is an extended, improved and corrected version of the preliminary approach presented in the MSc thesis report (van Aggelen, 2022); in particular, in the current paper, the friction model is corrected, the degradation model covers both asphalt concrete and porous asphalt and the exposition has been improved.

The contributions of the current paper to the state of the art are that an approach is proposed to optimize M&R of a pavement system, a model is used to predict states, and optimal M&R methods are found using numerical optimization methods. Furthermore, the effect of maintenance actions on states or damages can be chosen individually and model inaccuracies can be included, and also a good computational efficiency is obtained. Moreover, there is no limit to the number of components, and any pavement material and any M&R method can be implemented if the effects of these M&R methods can be modelled.

3. Pavement condition model

In this section, the condition model is developed. The model is built up from a state-space model, which includes degradations and the effects of maintenance actions. Starting from the continuous-time degradation models, it is shown how these can be converted into a discrete-time state-space model so it can be used in an MPC approach. Discrete time shows a sequence of sampled points in time, where the time intervals between two samples is the sampling time. In this section, the conversion is presented for the specific, illustrative degradation model presented in Section 3.2. Any other degradation model can be adapted for use in the proposed optimisation-based maintenance scheduling approach in a similar way.

3.1. Discrete-time state-space model for the condition

For nonlinear discrete-time dynamic models subject to uncertainty, the preferred general formulation is a state-space model (Meadows & Rawlings, 1997; Pearson & Kotta, 2004):

$$x(k+1) = f(x(k), u(k), \theta(k)) \tag{1}$$

$$y(k) = g(x(k), u(k), \theta(k)) \tag{2}$$

Here $x(k)$ is the state of the system at time step k, $u(k)$ is the input vector, $\theta(k)$ represents the uncertainties, f is the function describing the state update behaviour and g is the function describing the output behaviour in our case. In our case, the state or condition, $x(k)$ as given in Equation (1) is subject to natural degradation and the condition changes if we apply maintenance interventions. The road network can be divided into n components, where each component can be considered as a separate part of the road that can have different degradation parameters in the same condition model, similar to the model of Su (2018) and Su et al. (2017). This implies that for each component, the optimal maintenance strategy can be determined. The condition of the total asset can be described with a vector $x(k) \in \mathscr{X}$. We consider the most 5 dominant degradations of the pavement (see next section), so the dimensions of $x(k)$ are $6n \times 1$:

$$x(k) = (\underbrace{x^T_{\text{con},1}(k)\, x^T_{\text{aux},1}(k)}_{x^T_1(k)} \dots \underbrace{x^T_{\text{con},j}(k)\, x^T_{\text{aux},j}(k)}_{x^T_j(k)} \dots \underbrace{x^T_{\text{con},n}(k)\, x^T_{\text{aux},n}(k)}_{x^T_n(k)})^T \tag{3}$$

Here $x_{\text{con},j}(k)$ is a vector describing all the 5 considered conditions of component j at time step k:

$$x_{\text{con},j}(k) = \begin{pmatrix} x_{\text{C},j}(k) & x_{\text{R},j}(k) & x_{\text{L},j}(k) & x_{\text{T},j}(k) & x_{\text{F},j}(k) \end{pmatrix}^T \tag{4}$$

where the index C stands for cracks, R for ravelling, L for longitudinal unevenness, T for transverse unevenness and F for friction. The condition vector can easily be changed to accommodate other degradation types and also the number of degradation types can be changed. The vector $x_{\text{aux},j}(k)$ is a memory component that is used to model a changing (usually decreasing) effect for the same maintenance actions. For example, if a maintenance action like filling cracks has a sufficient effect for the first cracks, later interventions with the same action may have less effect as the repaired surfaces will be larger and have different properties.

Let us denote the set of all possible maintenance options with

$$\mathscr{A} = \{a_0, a_1, \dots, a_N\} \tag{5}$$

Here a_0 is defined as no intervention and a_N is a full renewal of the top layer. Next let us define the input vector:

$$u(k) = (u_1(k) \dots u_j(k) \dots u_n(k))^T \in \mathscr{A}^n \tag{6}$$

as the maintenance intervention that can be applied at the total asset at time step k. We can define $u_j(k) \in \mathscr{A}$ as the maintenance intervention that is applied to component j at time step k, while $u_j(k) = l$ indicates that the maintenance option a_l is applied. In a similar way, we can define the uncertainties, caused by model inaccuracies and measurement errors, by

$$\theta(k) = (\theta^T_1(k) \dots \theta^T_j(k) \dots \theta^T_n(k))^T \in \Theta^n \tag{7}$$

For the stochastic dynamics of component $j \in \{1, \dots, n\}$ of the pavement, Equations (1)–(2) can be written as

$$x_j(k+1) = f_j(x_j(k), u_j(k), \theta_j(k)) \tag{8}$$

$$= \begin{cases} f^0_j(x_j(k), \theta_j(k)) & \text{if } u_j(k) = a_0 \text{ (no maintenance)} \\ f^q_j(x_j(k), \theta_j(k)) & \text{if } u_j(k) = a_q \text{ with } q \in \{1, \dots, N-1\} \\ f^N_j(\theta_j(k)) & \text{if } u_j(k) = a_N \text{ (renewal)} \end{cases} \tag{9}$$

When no maintenance is performed, the condition of the pavement changes, i.e. it degrades. This is described by $f_j^0(x_j(k), \theta_j(k))$. With regard to outputs, we are interested in all states, so we consider $x(k)$ only, which is equivalent to setting $y(k) = x(k)$.

3.2. Continuous-time degradation models

In Leegwater (2019), a comprehensive overview is given for degradation models specifically developed for asphalt-concrete pavements in the pavement system in the Netherlands. The most suitable models with relevant parameter values for most degradations that are mentioned in Leegwater (2019) are found in de Groot (2002), which is the end report of a research programme for degradations on asphalt-concrete pavements in the Netherlands, where the degradation models are found from regression on measured data over a very long time span. The most suitable degradation model for friction in Leegwater (2019) is described in Kuijper (2014). The degradation model for longitudinal unevenness, as described in de Groot (2002) is based on the model in Office for Official Publications of the European Communities Eur-OP (1999). So the most suitable models for the dominant degradations are

Cracks $$\mu_{C,j}(t) = \left(\alpha + b_{\mathrm{C}} A_j + \beta_{\mathrm{k}} + c_{\mathrm{v}} V_j\right)(t - t_0) + a_{\mathrm{C}} A_j + \alpha_{\mathrm{k}} \quad (10)$$

Ravelling $$\mu_{R,j}(t) = \theta(1 - \mathrm{e}^{-\lambda(t - t_0 - \tau_p)}) \quad (11)$$

Longitudinal unevenness $$\mu_{L,j}(t) = a_{\mathrm{L}} + b_{\mathrm{L}}(t - t_0) \quad (12)$$

Transverse unevenness $$\mu_{T,j}(t) = a_{\mathrm{T}} + b_{\mathrm{T}}(t - t_0) \quad (13)$$

Friction (skid resistance) $$\mu_{F,j}(t) = a_{\mathrm{F}} + b_{\mathrm{F}} \log_{10}(\mathrm{q}\,(t - t_0)/365) \quad (14)$$

These degradation models are in continuous time with t in years from new condition ; moreover, these are not update models as the condition at a specific time instant is provided directly. All these degradations result in increasing values in time, while the value for friction is decreasing in time. The units in Equations (10)–(14) are m cracks/100 m road for $\mu_{C,j}(t)$, % area stone loss for $\mu_{R,j}(t)$, m/km road for $\mu_{L,j}(t)$ and mm for $\mu_{T,j}(t)$, while $\mu_{F,j}(t)$ is unitless. Furthermore, A_j is the thickness of the asphalt on section j in mm, V_j the truck intensity in trucks per lane per day, θ the maximum value for ravelling and q the traffic intensity in million vehicles per lane per year. All other variables are coefficients and their values are listed in Table 1.

One has to be careful using input parameters that are outside the range for which the models that have been developed in de Groot (2002) and Kuijper (2014), were found, e.g. very low traffic or high traffic loads or extreme soil settlements. By moving all degradations as mentioned in Equations (10)–(14) into a vector, the models are transformed into one single model. The vector containing all degradations of component j at time t can be written as

$$\mu_{\mathrm{deg,c},j}(t) = \begin{pmatrix}\mu_{C,j}(t) & \mu_{R,j}(t) & \mu_{L,j}(t) & \mu_{T,j}(t) & \mu_{F,j}(t)\end{pmatrix}^T \quad (15)$$

The index deg,c indicates this is the degradation in continuous time.

Table 1. Parameters used for the degradation model.

Damage form	Parameter	Value AC	Value PA	Units
Cracks	a_c	−0.000513	−0.000513	–
	A	50	60	mm
	b_c	−0.000121	−0.000121	–
	c_v	0.0000448	0.0000448	–
	V	4000	6000	trucks/lane/day
	α	0.159	0.159	–
	α_k	0	−1.003	–
	β_k	0	−0.160	–
	c_v	0.0000448	0.0000448	–
Ravelling	θ	1.52	4.41	–
(standard scenario)	λ	0.160	0.220	–
	τ_p	0	3	year
Longitudinal	a_L	0	0	–
unevenness	b_L	0.033	0.033	–
Transverse	a_T	0	0	–
unevenness	b_T	0.668	0.668	–
Friction	a_F	0.481	0.47	–
	b_F	−0.0384	−0.0845	–
	q	10.95	14.60	10^6vehicles/lane/365 days

The model, as described in Equation (15), is used in the remainder of this paper to develop and illustrate the proposed M&R optimisation approach without loosing generality, as other models for other countries, or other asphalt types can easily be used instead.

3.3. Conversion of the continuous-time degradation model into a discrete-time degradation model

In this section, Equation (15), which represents the degradation model Equations (10–14), is converted from continuous time to discrete time, so that it can be used in the condition model Equations (1)–(3). The condition at time t can be determined by the addition of the original condition and the degradation in the time duration:

$$x_{\text{con,c},j}(t) = x_{\text{con,c},j}(t_0) + \mu_{\text{deg,c},j}\,(t - t_0) \quad \forall\, t \geq t_0 \tag{16}$$

where $x_{\text{con,c},j}(t)$ is the condition at time t, t_0 is the time at which the condition is x_0, and $\mu_{\text{deg,c},j}$ is the vector containing all degradations on component j. If we choose the time step k as one month, which is sufficient as the degradation dynamics are slow, then $t = 12\,k$, so the 5×1 updated condition vector for component j in discrete time, at time step $k+1$, can be found with

$$x_{\text{con},j}(k+1) = x_{\text{con},j}(k) + \mu_{\text{deg},j}(k) \tag{17}$$

We can define two points of time, t_1 and t_2 and insert these in Equation (16). If we substitute one of the resulting equations in the other and substitute $t_0 = k_0/12, t_1 = (k+1)/12, t_2 = k/12$ in the resulting equation, we find:

$$\mu_{\text{deg},j}(k) = \mu_{\text{deg,c},j}((k+1-k_0)/12) - \mu_{\text{deg,c},j}((k-k_0)/12) \tag{18}$$

3.4. Modelling maintenance actions

When a maintenance intervention $u(k)$ is done at time step k, the condition is reset. The change of the condition depends on the type of intervention. We can define elements of the condition vector $x_{\mathrm{con},j}(k)$ of component $j \in \{1, \dots, n\}$ after a maintenance intervention $u_j(k)$ by

$$x_{i,j}(k+1) = \begin{cases} \phi_{i,j}(k) & \text{for } u_j(k) = a_N \\ \psi_{i,j,q}\, x_{i,j}(k) & \text{for } u_j(k) = a_q \text{ with } q \in \{1, \dots N-1\} \end{cases} \tag{19}$$

for $i \in \{\mathrm{C, R, L, T, F}\}$. Here $x_{i,j}(k)$ is the value of the damage, as described in Equation (4), $u_j(k)$ is the maintenance action, applied at component j at time step k and q is the index for the maintenance option (see Equation (9)) and n is the number of components. In the case of cracks, ravelling, longitudinal unevenness, transverse unevenness, $0 < \psi_{i,j} \leq 1$ if $i \in \{\mathrm{C, R, L, T}\}$, while for friction $\psi_{\mathrm{F},j} > 1$. The degradation continues if there is no change in condition from a maintenance intervention, hence the use of $(k+1)$ for those conditions. For specific values of conditions after intervention see the Case study, Section 6.

4. Model for maintenance optimisation

In this section, a framework for the optimisation model is presented. With this model, conditions caused by degradation and maintenance interventions can be predicted, while the optimisation method can determine actions on optimal moments so that a predefined cost function is minimised.

4.1. Prediction model

To run the chosen optimisation, we have to be able to predict or estimate, future states and inputs. The estimated states $\tilde{x}(k)$, control inputs $\tilde{u}(k)$ and uncertainties $\tilde{\theta}(k)$ can be described with

$$\tilde{x}(k) = (\hat{x}^T(k+1|k) \dots \hat{x}^T(k+N_\mathrm{p}|k))^T \tag{20}$$

$$\tilde{u}(k) = (u^T(k) \dots u^T(k+N_\mathrm{p}-1))^T \tag{21}$$

$$\tilde{\theta}(k) = (\theta^T(k) \dots \theta^T(k+N_\mathrm{p}-1))^T \tag{22}$$

Here is $\hat{x}(k+1|k)$ the predicted state at time step $k+1$, based on the information known at time step k and N_p is the prediction horizon. Based on Equation (1), the N_p step prediction model can be written

$$\tilde{x}(k) = \tilde{f}(x(k), \tilde{u}(k), \tilde{\theta}(k)) \tag{23}$$

Here the function $\tilde{f}$ can be found by recursive substitution as done in MPC.

4.2. Constraints

As mentioned earlier, an advantage of MPC is that constraints can be set to inputs, states or output variables. The constraints can be written as

$$\tilde{g}(x(k), \tilde{u}(k), \tilde{\theta}(k)) \leq 0 \tag{24}$$

We can have local constraints, which are valid for some parts of the system and global constraints, which are valid for the total system. Examples of global constraints are an upper bound on the total costs or the maximum number of times maintenance can be done to a road or the maximum number of roads that can be maintained on a certain moment. Moreover, equality constraints and non-equality constraints can be used. The function $\tilde{g}$ can be found in a similar way as $\tilde{f}$ in Equation (23). The linear constraints for the time instants can be defined as

$$(t_{j,k})_1 \geq k \quad \forall j \in \{1,\ldots,n\} \tag{25}$$

$$(t_{j,k})_M \leq t_{j,k}^{\max} \quad \forall j \in \{1,\ldots,n\} \tag{26}$$

$$(t_{j,k})_{i+1} - (t_{j,k})_i \geq \Delta\, t_j^{\min} \quad \forall j \in \{1,\ldots,n\}\, \forall i \in \{1,\ldots,M-1\} \tag{27}$$

$$t_{j,k}^{\max} = k + N_\mathrm{p} + 1 + M\Delta\, t_j^{\min} \quad \forall j \in \{1,\ldots,n\} \tag{28}$$

k is fixed at each optimisation step. The lower bound of the time instants for the first intervention on component j is described in Equation (25). In Equation (26), the upper bound is described, which can be calculated from Equation (28) and allows for not having an intervention at all. In Equation (27) $\Delta\, t_j^{\min}$ describes the minimum interval between two interventions. Finally, in Equation (28), the upper bound is calculated. This upper bound is reached if the optimisation does not put any action within the prediction period, so all remaining actions will have to take place right after this. Next to these constraints, also other constraints can be added to the time instants, like an upper bound on the total maintenance cost or one or more conditions of the asset can be bound. These constraints must be considered at each step of the optimisation and can be considered deterministic.

4.3. Time-instant-optimisation

Often when optimisation methods are applied to systems with both discrete and continuous dynamics, a direct optimisation approach is used. The process will find the optimal new actions at each time step, and it will decide for every action the exact moment and duration between actions. Another approach is the Time-Instant-Optimisation (TIO) approach (De Schutter & De Moor, 1998; Su, 2018; Su et al., 2017), where for each intervention, the control action and the length of the intervals between the interventions are calculated. This method is non-smooth, but continuous and less calculation effort is required compared to direct optimisation. In Figure 1, an example is shown that makes the difference between both methods clear; for the case, direct optimisation is used, an array of 22 time steps has to be optimised, while in the TIO approach, an array of 3 steps has to be optimised. This results in a more efficient calculation effort in the TIO case.

In TIO, the input vector $u(k)$, as described in Equation (6), is changed to time instants $\tilde{t}(k)$ and an action vector $\tilde{v}(k)$, where the tilde denotes a predicted stacked input. The maintenance options are chosen from $\mathscr{A}$, as described in Equation (5), but the option no maintenance a_0 is excluded, so degradation continues if no maintenance is done. We can write all the time instants that have to be optimised for the total system in a similar way as in Equations (6) and (7):

$$\tilde{t}(k) = (\tilde{t}_1^T(k) \ldots \tilde{t}_j^T(k) \ldots \tilde{t}_n^T(k))^T \tag{29}$$

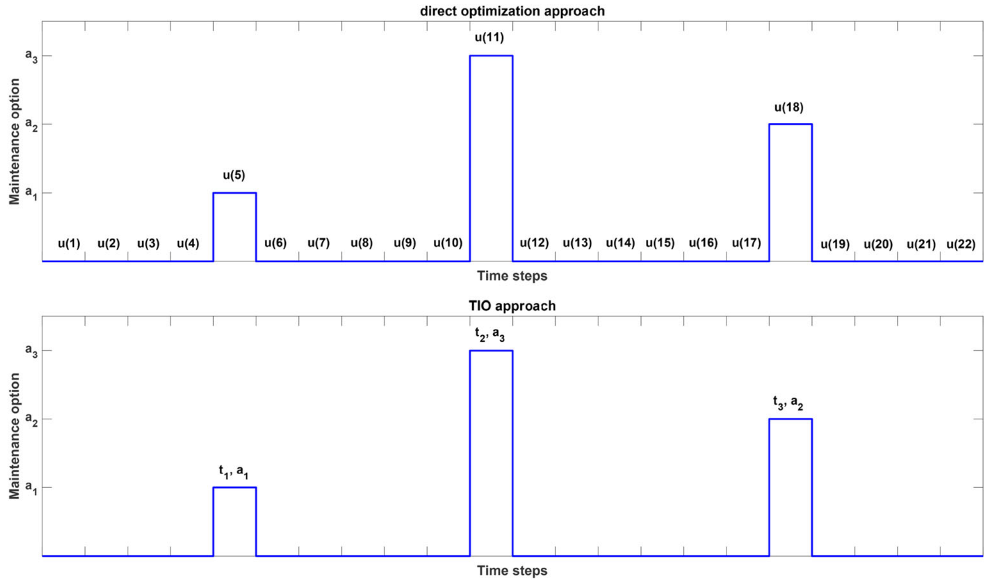

Figure 1. Maintenance actions for direct optimisation (upper) and TIO (lower) approaches, based on (Su et al., 2017).

where the time instants $\tilde{t}_j(k)$ for each component can be written as

$$\tilde{t}_j^T(k) = (t_{j,1}(k) \dots t_{j,r}(k) \dots t_{j,M}(k))^T \tag{30}$$

The corresponding maintenance action vector $\tilde{v}(k)$ is similar to Equation (29):

$$\tilde{v}(k) = (v_1^T(k) \dots v_j^T(k) \dots v_n^T(k))^T \in (\mathscr{A} \setminus \{a_0\})^{n\times M} \tag{31}$$

Also, the vector $\tilde{v}_j^T(k)$ for each component is similar to Equation (30):

$$\tilde{v}_j^T(k) = (v_{j,1}(k) \dots v_{j,i}(k) \dots v_{j,M}(k))^T \in (\mathscr{A} \setminus \{a_0\})^M \tag{32}$$

where M is the maximum number of maintenance interventions. In TIO, which we use in the current paper, a_0 (no maintenance) is not used, but it indicates the degradation, so we use $\mathscr{A} \setminus \{a_0\}$. Each intervention thus represents a time instant $t(k)$ with a corresponding maintenance action $v(k)$ from a selected number of maintenance options $a_l \in \mathscr{A} \setminus \{a_0\}$.

How the found time instants and their corresponding maintenance interventions are converted into real actions, is explained with an example. Let us assume that we have one component j and 4 maintenance options, so $\mathscr{A} \setminus \{a_0\} = \{a_1, a_2, a_3, a_4\}$. At control time step k a time instant vector $t(k) = (t_1(k) \;\; t_2(k) \;\; t_3(k) \;\; t_4(k))^T$ and the vector with interventions $v(k) = (v_1(k) \;\; v_2(k) \;\; v_3(k) \;\; v_4(k))^T = (a_2 \;\; a_1 \;\; a_3 \;\; a_4)^T$ are found, see Figure 2.

At every control time step k, the optimisation method takes the constraints according to Equations (25)–(28) into account. In this example, the minimum interval Equation (27) is 1 time step. As shown in Figure 2, two interventions are found after the prediction horizon, which means the two first interventions will be performed within the prediction window only: (t_1, a_2) and (t_2, a_1). The optimisation method is performed again and at the next time step new actions may be found.

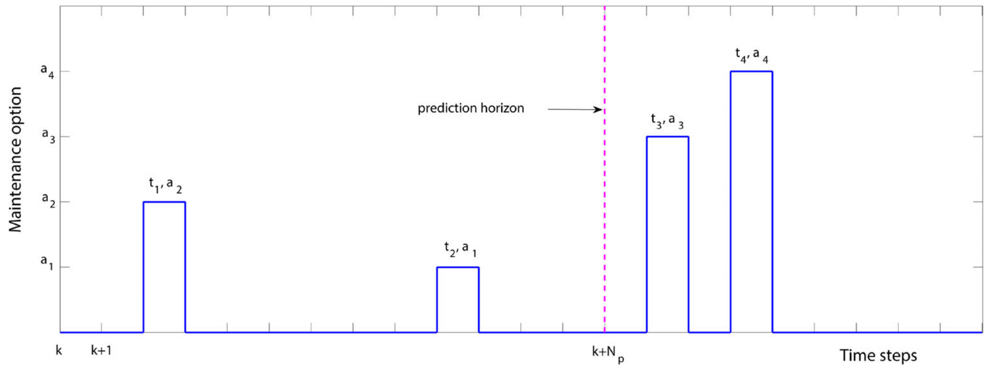

Figure 2. An example of converting maintenance actions in the prediction window.

4.4. Cost function

The optimisation involves a minimisation of the cost function. This cost function contains direct costs, such as maintenance costs but also other costs can be assigned. Examples are costs we can assign to degradation, traffic safety, environmental matters or recyclability. In the case, we optimise both maintenance and degradation costs, the cost function that has to be minimised at each control time step k, looks like

$$J(k) = J_{\text{maint}}(k) + J_{\text{deg}}(k) \tag{33}$$

The cost for maintenance is the sum of all individual maintenance interventions that is performed. As discussed in the previous section, the optimisation method determines the optimal time instants and optimal maintenance actions.

We have:

$$J_{\text{maint}}(k) = \sum_{j=1}^{n} \sum_{l=1}^{N_{\text{p}}} \sum_{q=1}^{N} \gamma_{jq} \, I_{u_j(k+l-1)=a_q} \tag{34}$$

where the binary indicator function is defined as follows: $I_X = 1$ in case X is true or else $I_X = 0$. The factor γ_{jq} converts I_X to a maintenance cost, which can be different for each component and is different for each intervention a_q.

The cost we can assign to the degradation is the sum of all conditions at each time step, compared to an ideal condition. This can be different from the condition from new or after an intervention. This means that if a condition is further away from this ideal condition, the contribution to the cost is larger and the optimisation method tries to keep these contributions as small as possible. The cost we can assign to the degradation of the pavement is

$$J_{\text{deg}}(k) = \sum_{j=1}^{n} \sum_{l=1}^{N_{\text{p}}} \Lambda_j^T \, |\hat{x}_{\text{con},j}(k+l) - \underline{x}_{\text{con},j}| \tag{35}$$

In Equation (35), the absolute difference between the predicted condition and the ideal condition $\underline{x}_{\text{con},j}$, e.g. the initial condition of a new road after fabrication assuming the fabrication has been done right, is calculated. The vector Λ_j consists of $5j$ elements that are made from weights for and scaling of the conditions. With Λ_j, we can also bring the cost to a value that is comparable to the maintenance cost. How Λ_j can be determined is discussed in the next section.

4.5. Scaling and weights for degradation costs

Over a certain period, some damages can change a lot more in value than other damages. With scaling all conditions are converted to a comparable scale and such that they have comparable contributions to the cost function. Each scaling factor $s_{i,j}, i \in \{C,R,L,T,F\}$ affects the corresponding row of the predicted condition vector $\hat{x}_{con}$ (see Equation (35)), and is defined as

$$s_{i,j} = \begin{cases} \dfrac{1}{x^{max}_{con,i,j} - \underline{x}_{con,i,j}} & \text{for } i \in \{C,R,L,T\} \\ \dfrac{1}{\underline{x}_{con,i,j} - x^{min}_{con,i,j}} & \text{for } i = F \end{cases} \tag{36}$$

where $x^{max}_{con,i,j}$ is the maximum value the degradation reaches, $\underline{x}_{con,i,j}$ is the best possible condition, $x^{min}_{con,i,j}$ is the lowest value for friction. With Equation (36), every contribution is normalised near the interval $[0, 1]$. Also, a factor $l_{i,j}$ is introduced to map the normalised cost to a monetary cost. After scaling, we could choose to let some degradations that are considered more important, have more weight in the contribution to the cost function; this is expressed with a weight $w_{i,j}$. To bring the cost of degradation to a level that makes a comparison with the real maintenance realistic in size and units (euro in this report), a factor is $l_{i,j}$ is introduced. So finally the elements of Λ_j can be written as

$$\lambda_{i,j} = s_{i,j}\, w_{i,j}\, l_{i,j} \quad \text{for } i \in \{C,R,L,T,F\} \tag{37}$$

4.6. Final time step

The optimisation is usually done for a limited time. The end time can be defined by the end of a long-term planning period, the expected lifetime of the pavement or the end of a maintenance contract. The final time step of the optimisation is called k_{end} in Figure 3. The optimisation process can also be interrupted in cases where the model or constraints are no longer valid.

5. Defining the optimisation problems

The objective function that has to be optimised, is the cost function Equation (33) and can be written as a function of the condition, inputs and uncertainties: $J(k) = F(x(k), \tilde{t}(k), \tilde{v}(k), \tilde{\theta}(k))$.

5.1. Deterministic TIO

Let us introduce a nominal inaccuracy $\tilde{\theta}_{nom}$. If we combine the prediction model Equations (20)–(23) with this function for $J(k)$, the optimisation problem (including costs and

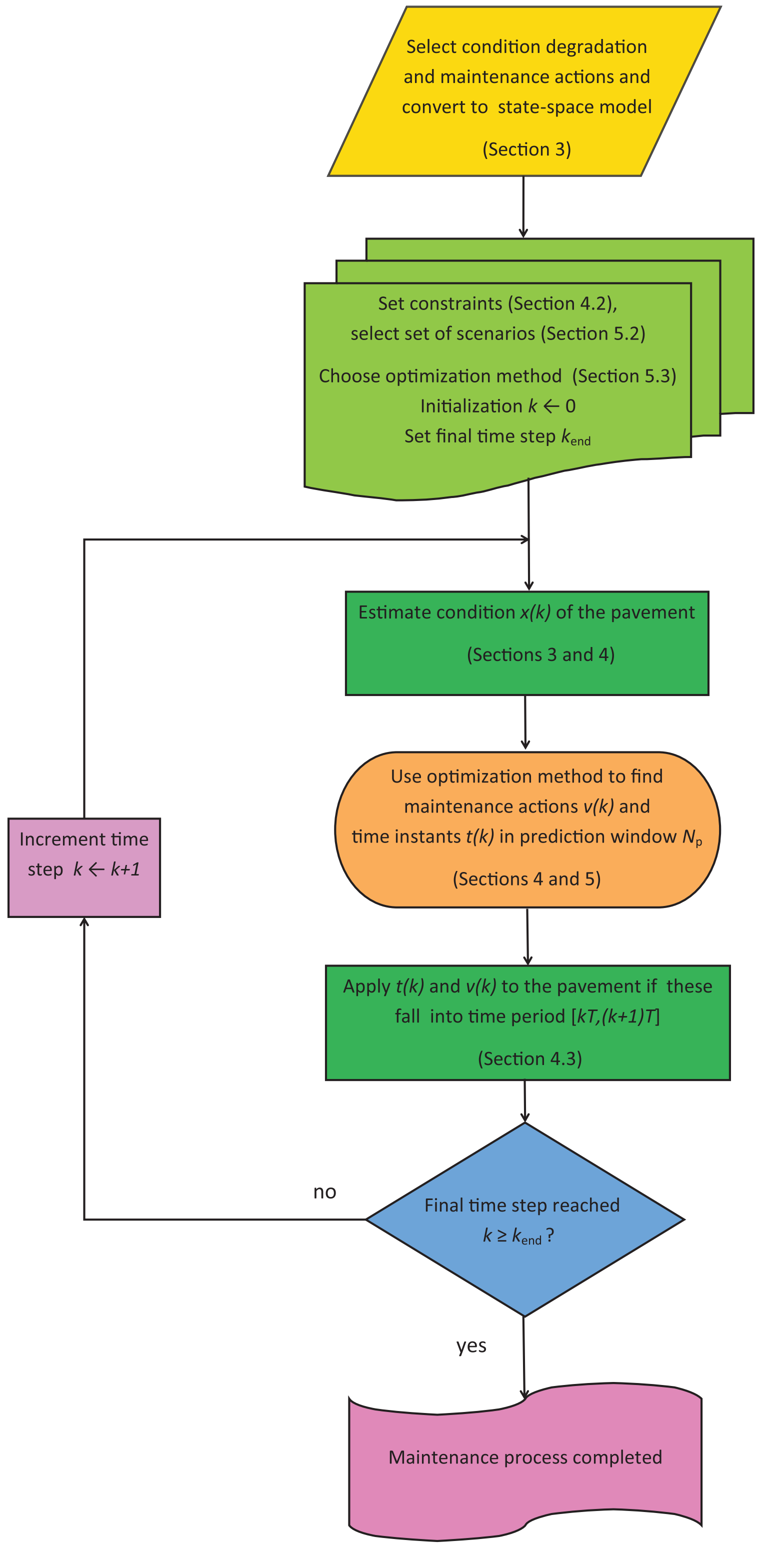

Figure 3. Flowchart of the proposed maintenance optimisation approach.

constraints) in the deterministic case, can be described as follows:

$$\min_{\tilde{t}(k),\tilde{v}(k)} f_{\text{TIO}}(x(k), \tilde{t}(k), \tilde{v}(k), \tilde{\theta}_{\text{nom}}) \tag{38}$$

$$\text{subject to}: \tilde{g}_{\text{TIO}}(x(k), \tilde{t}(k), \tilde{v}(k), \tilde{\theta}_{\text{nom}}) \leq 0 \tag{39}$$

Here, the function $\tilde{g}_{\text{TIO}}$ represents all bounds and constraints.

5.2. Scenario-based TIO

In real-life situations, uncertainties are not precisely known. When uncertainties exist, the expected value of the cost function has to be considered and the constraints can be replaced with chance constraints. With chance constraints, the constraints are met with a given probability, no less than a given confidence level. We call this confidence level: constraint violation threshold. With chance constraints, conservatism that arises with worst-case scenarios as is used in robust approaches, can be avoided. The chance-constrained TIO problem looks like

$$\min_{\tilde{t}(k),\tilde{v}(k)} \mathbb{E}_{\tilde{\theta}} \left(f_{\text{TIO}}(x(k), \tilde{t}(k), \tilde{v}(k), \tilde{\theta}(k)) \right) \tag{40}$$

$$\text{subject to}: \mathbb{P}_{\tilde{\theta}} \left(\tilde{g}_{\text{TIO}}(x(k), \tilde{t}(k), \tilde{v}(k), \tilde{\theta}(k)) \leq 0 \right) \geq 1 - \eta \tag{41}$$

If the probability distributions of the system are all known, then the probability distribution of θ can be determined. The set of all possible realisations over the prediction period, $\tilde{\Theta} = \Theta^{N_\text{p}}$ is huge. An analytical computation of the optimum is usually not possible as the problem is non-linear and non-convex and a numerical computation takes a lot of computational effort because of the huge number of realisations. To improve tractability, we can select a limited number of scenarios; let us denote this subset $\tilde{h} \in \tilde{\mathscr{H}} \subset \tilde{\Theta}$. We define $p_{\tilde{h}}$ as the probability of scenario $\tilde{h} \in \mathscr{H}$, while $\sum p_{\tilde{h}} = 1$. The scenario-based optimisation problem is then defined as

$$\min_{\tilde{t}(k),\tilde{v}(k)} \sum_{\tilde{h}\in\tilde{\mathscr{H}}} p_{\tilde{h}} f_{\text{TIO}}(x(k), \tilde{t}(k), \tilde{v}(k), \tilde{h}) \tag{42}$$

$$\text{subject to}: \sum_{\tilde{h}\in\tilde{\mathscr{H}}} p_{\tilde{h}} I_{\tilde{g}_{\text{TIO}}(x(k),\tilde{t}(k),\tilde{v}(k),\tilde{h})\leq 0} \geq 1 - \eta \tag{43}$$

The working of this approach is illustrated in Figure 3, and in a case study in Section 6.

5.3. Optimisation methods

The optimisation problems, as described in Equations (38)–(43) are generic. The time part of the result of the optimisation method in our case is rounded to the nearest value at every time step, which makes it a non-smooth process. As the optimisation is also non-convex with constraints, derivative-free or direct search methods, like pattern search or genetic algorithms, should be used. Both methods can bring comparable results with multiple starting points or multiple runs, although in some cases one of the methods may perform better. Genetic algorithms can work with discontinuous cost functions, while pattern search can fail at discontinuities (Wetter & Wright, 2003). In Su et al. (2017) pattern search with multi-start is used, while in the case study of the current paper, genetic algorithms are used. More information on genetic algorithms can be found in Goldberg (1989), Conn et al. (1991, 1997) and Nieminen et al. (2003).

6. Case study

In this section, a case study is presented to assess and to illustrate the maintenance optimisation approach. Representative values are used for the input variables, such as traffic intensities and model parameters. Furthermore, we look at two different asphalt types: Asphalt Concrete (AC), which is used mostly on secondary road networks, and Porous Asphalt (PA), which is used mostly on main road networks. The damages and maintenance options for both types of asphalt are very different, and the use of both types of asphalt in this case study gives a better understanding of and insight in the approach developed in this paper.

6.1. Set-up

We start with the set-up, parameter choice and show how the model is constructed. The optimisation is performed for the deterministic case, as described in Section 5.1, and for the scenario-based case, as described in Section 5.2. In this case study, we assume all interventions can take place at any chosen moment, and in any order. For readability, the number of components is limited to 1. The length of this component is not relevant as we look to the costs per km, but we consider it to be long enough to have representative degradation costs and maintenance costs.

We simulate two different roads: one with a top layer made of Asphalt Concrete (AC) and another with Porous Asphalt (PA). The traffic and truck intensities are common and chosen from Rijkswaterstaat (2012). We can substitute the values, as can be found in de Groot (2002) (see Table 1) into the degradation model Equations (10)–(14) we introduced in Section 3.2 and rework these according to Section 3.3. The state update model used for degradation is

$$x(k+1) = \begin{pmatrix} x_{\mathrm{C}}(k) + (\alpha + b_{\mathrm{C}} A + \beta_{\mathrm{k}} + c_{\mathrm{v}} V)/12 \\ x_{\mathrm{R}}(k) + \theta\, \mathrm{e}^{\lambda\tau}\, (\mathrm{e}^{-\lambda(k_{\mathrm{s}1}-k_0-1)} - \mathrm{e}^{-\lambda(k_{\mathrm{s}1}-k_0)}) \\ x_{\mathrm{L}}(k) + b_{\mathrm{L}}/12 \\ x_{\mathrm{T}}(k) + b_{\mathrm{T}}/12 \\ x_{\mathrm{F}}(k) - b \log_{10}((k_{\mathrm{s}2} - k_0 + 1)/(k_{\mathrm{s}2} - k_0)) \end{pmatrix} \tag{44}$$

The time steps $k_{\mathrm{s}1}$ and $k_{\mathrm{s}2}$ are shifted compared to the normal time step k, as these need to be reset after an intervention for ravelling and friction, respectively. Furthermore, the values for $x_{\mathrm{R}}(k)$ and $x_{\mathrm{F}}(k)$ have to be initialised for $k = 1$. Because $\log(q \times k) = \log q + \log k$, the variable q and constants are captured within the initialisation.

The prediction horizon, which is the time the controller looks ahead at each time step, is set to 24 time steps, i.e. 2 years. The endpoint of the simulation is set at 360 time steps, which is 30 years. This means the approach in this paper predicts the conditions and costs over 30 years. Deterministic TIO assumes there is only one scenario, and in scenario-based TIO, every scenario occurs with a given probability (see Section 5.2); reality may be described with more scenarios. To demonstrate the flexibility in the presented approach, we include three scenarios next to the standard scenario. With the inclusion of scenarios, changes in future conditions can be modelled. Because of space limitations in this paper, we only perform the optimisation with a perfect scenario prediction (the time and duration of every scenario is described and the simulation includes the same scenarios), which is defined, as shown in Table 2. We assume there is no interaction between interventions, i.e. the reset states can be chosen independently, and we assume there is no decrease in the effect of maintenance, so $x_{\text{aux},j}$ is omitted. The cost and the effect of the maintenance actions that are modelled according to Equation (19) can be seen in Table 3. The negative values for rejuvenation are to create the incubation time τ in the calculation; these are converted to zero for the condition vector. As rejuvenation is not effective for large values for ravelling, the upper bound for applying rejuvenation is set to 2. In this case study, the 'as new' condition is used as the initial condition, which is found by calculating Equation (44) with all correct values and $k = 1$: $x(1) = (0\ \ 0.0201\ \ 0\ \ 0\ \ 0.5809)^T$ for AC and $x(1) = (0\ \ -3.9677\ \ 0\ \ 0\ \ 0.6793)^T$ for PA. All weights have the same value, so as $j = 1$: $w_{i,1} = 1\ \forall\, i$. The elements of the scaling vector $s_{i,1}$, as presented in Equation (36), are chosen as $s_{i,1} = (4\ \ 2\ \ 0.5\ \ 10\ \ 0.15)$. The value $l_{i,1}$ (see Equation (37)) is set to 200 for every degradation, which results in a degradation cost that is similar to the maintenance cost, as found by the optimisation approach. For the constraints as described in Equations (25)–(28), the minimum interval between two interventions, $\Delta\, t_1^{\text{min}}$, is set to 6. The minimum time instant for an intervention to take place, $t_{1,k}^{\text{min}}$, is set to 1 and the maximum time instant $t_{1,k}^{\text{max}}$, is set according to Equation (28). Furthermore, all lower bounds for $\tilde{t}(k)$ (see Equation (29)) are set to $(0\,0\,0\ \ 0)^T$ and for $\tilde{v}(k)$ the lower bounds are set to $(1\ 1\ 1\ 1)^T$. The bounds on the conditions are set as $x_\text{C}(k) \le 6, x_\text{R}(k) \le 4, x_\text{L}(k) \le 2, x_\text{T}(k) \le 15, x_\text{F}(k) \ge 0.40\ \forall\, k$ for AC. For PA, the upper bound for ravelling is set to 5, while the rest is the same as for AC. These values are in the classes 'light' to 'moderate' in the current maintenance strategy, except for friction where 0.39 is considered a lower limit to ensure safety (Vos, 2015). The constraint violation threshold η for the chance-constraints, as discussed in Section 5.2 is set to 0.05.

6.2. Software and hardware used

The developed approach is simulated in MATLAB R2024b and the genetic algorithms from the Global Optimisation toolbox in MATLAB R2024b is used to find the optimum. The software runs on a PC with Windows 10 (64 bit) operating system, on Intel Core i5-9500 CPU with 3.00 GHz clock frequency and 16 GB memory; for most runs with end time 360 months, around 30–45 minutes of total simulation and computation time are needed.

6.3. Results

Now closed-loop TIO for the deterministic and scenario-based cases is performed on roads made of AC and PA. See Figures 4 and 5 for plots of the evolution of the health conditions over time. In Table 4, all values for the time instants $\tilde{t}(k)$ and maintenance options $\tilde{v}(k)$ and also the closed-loop costs for degradation, the maintenance costs and total costs over the simulation period are shown. From Figures 4 and 5, it can be seen that PA has a much faster degradation for ravelling and for friction, compared to AC. This implies more maintenance is needed for PA: 2 times a renewal is needed for PA, whereas for AC 1 renewal is needed. For AC, the degradation costs and maintenance costs are similar for deterministic TIO and

Table 2. Scenarios and model parameters used in the case study.

Road	Number of lanes	Time from start [months]	Scenario	Traffic intensity [vehicles/lane/day]	Truck intensity [trucks/lane/day]	Ravelling θ	Soil stiffness [MPa]
AC	1	0–90	$\tilde{h}_1$	30,000	4000	1.52	130
		91–180	$\tilde{h}_2$	30,000	5320 (+33%)	1.52	130
		181–270	$\tilde{h}_3$	30,000	4000	1.824 (+20%)	130
		271–360	$\tilde{h}_4$	30,000	5320 (+33%)	1.824 (+20%)	130
PA	2	0–90	$\tilde{h}_1$	40,000	6000	4.41	130
		91–180	$\tilde{h}_2$	40,000	7980 (+33%)	4.41	130
		181–270	$\tilde{h}_3$	40,000	6000	5.292 (+20%)	130
		271–360	$\tilde{h}_4$	40,000	7980 (+33%)	5.292 (+20%)	130

Table 3. Possible maintenance interventions and their cost and effects on the condition of the pavement.

Road	Maintenance intervention $A \in \mathscr{A}$	Maint. cost [EUR/km]	Change in condition (see Equation (19))
AC	a_1 fill cracks	7000	$x_C(k+1) = (0.50\,x_C(k))$
	a_2 focused water blasting	8500	$x_F(k+1) = 0.58$
	a_3 surface treatment	34, 000	$x_{C,R,F}(k+1) = (0.70\,x_C(k)\ \ 0.40\,x_R(k)\ \ 0.56)$
	a_4 renewal top layer	60, 000	$x_{C,R,L,T,F}(k+1) = (0\ \ 0\ \ 0\ \ 0\ \ 0.5809)$
PA	a_1 rejuvenation	2500	$x_R(k+1) = -3.00$
	a_2 focused water blasting	8500	$x_F(k+1) = 0.66$
	a_3 renewal top layer	60, 000	$x_{C,R,L,T,F}(k+1) = (0\ \ -3.9677\ \ 0\ \ 0\ \ 0.6793)$

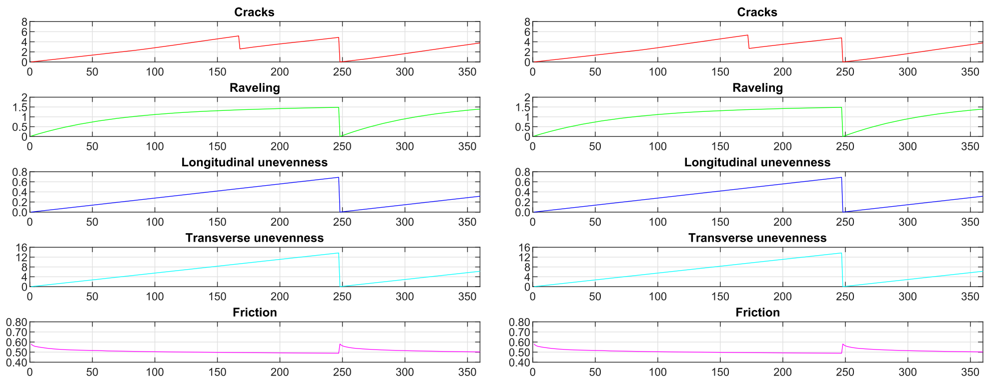

Figure 4. Deterministic TIO (left) and scenario-based TIO (right) on AC. For values of $\tilde{t}(k)$ and $\tilde{v}(k)$ see Table 4.

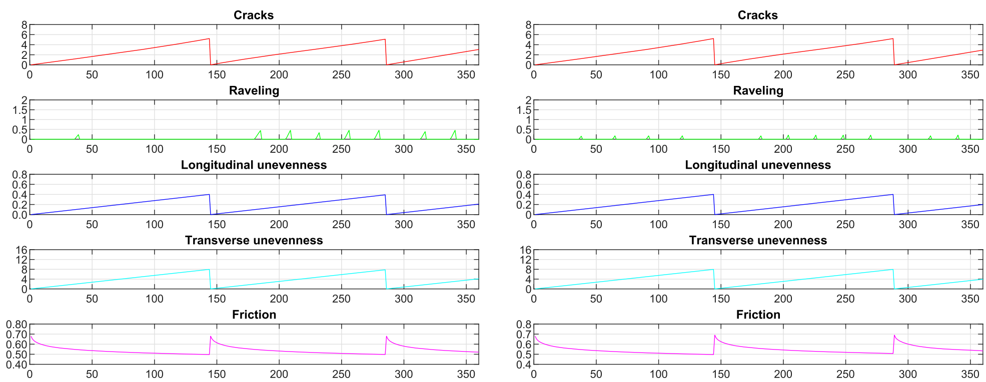

Figure 5. Deterministic TIO (left) and scenario-based TIO (right) on PA. For values of $\tilde{t}(k)$ and $\tilde{v}(k)$ see Table 4.

scenario-based TIO. For PA, both costs are also similar, but ravelling remains lower during the observation time in closed-loop TIO. The scales for all plots are the same for all situations; as a result, ravelling on PA in scenario-based TIO looks very small.

Table 4. Results of closed-loop TIO for different cases and parameters for AC and PA over entire simulation period.

Road	Optimisation method	Prediction horizon	Intervention moments	Maintenance option	Degradation cost EUR	Maintenance cost EUR	Total cost EUR
AC	deterministic	24	168,248	1,4	198,270	67,000	265,270
AC	scenario-based	24	173,248	1,4	198,590	67,000	265,590
PA	deterministic	24	39,64,89,114,139,144,185,209, 232,256,280,285,317,341	1,1,1,1,1,3,1,1,1,1,1,3,1,1	162,340	150,000	312,340
PA	scenario-based	24	39,66,93,120,145,183,205,227,249,271,289,319,341	1,1,1,1,3,1,1,1,1,1,3,1,1	159,740	147,500	307,240

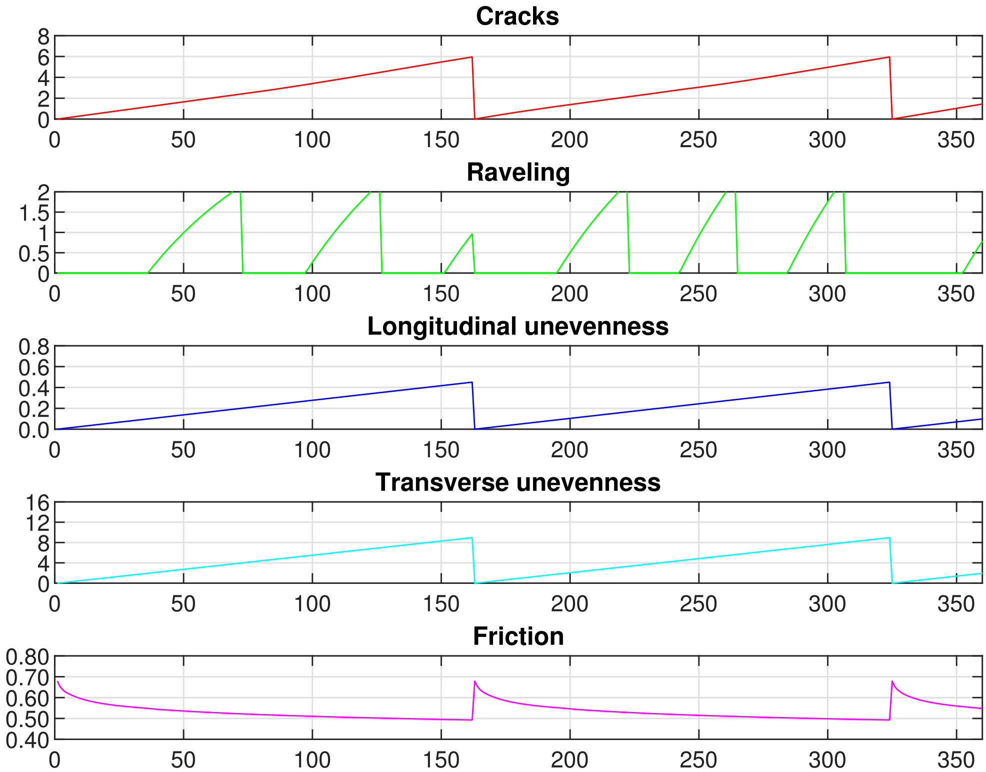

Figure 6. Current approach, with 6 months between inspections.

6.4. Comparison with current maintenance strategies

The method currently used in practice is condition-based and thorough inspections are then necessary. Besides this, much knowledge is needed for the interpretation of the results of the inspections. To compare the conceptual approach developed in this paper with the approach currently used in practice, a plot is made for a road made of PA, see Figure 6. The idea behind this plot is that from the start of the simulation, 6 steps are taken at a time, every 6 months (i.e. every 6 steps) an inspection takes place and the bounds are checked. The 6 months between each inspection resemble the current frequency of inspections as currently used in practice in the Netherlands. The bounds are the same as used in the closed-loop TIO approach to make the results comparable. If a degradation has exceeded a bound, maintenance is needed to reset that degradation. If more than one bound is passed, a maintenance option that resets more than one degradation may be needed.

We find $\tilde{v}(k) = (1, 1, 3, 1, 1, 1, 3)$ and $\tilde{t}(k) = (72, 126, 162, 222, 264, 306, 324)$, so five times option a_1 (rejuvenation) and two times option a_3 (renewal of the top layer). The total costs as defined in Equation (33) are 327,490 EUR per km in this case. For the deterministic TIO case with a prediction horizon of 24 time steps, we find a total cost of 312,340 EUR, while the maintenance cost is 150,000 EUR (see Table 4). This means that the optimisation method based on the deterministic TIO approach, as discussed in Section 5.1, finds a strategy that costs 15,150 EUR per km, which is 4.6% less expensive then the cost obtained with the method that is similar to the current strategy. The total yearly cost for management and maintenance in a country like the Netherlands is between 323 and 1231 million EUR each year (between 2008 and 2020) (Government of the Netherlands, 2020), so this percentage represents a substantial amount of money. Furthermore, with the conceptual approach, as developed in this paper, inspections can be done faster, easier and cheaper. Another benefit from the optimisation-based approach, is that the condition of the pavement can be predicted and a cost can be assigned to this condition. Although this can also be done with the life expectancy models, inspections and evaluations are still needed to do this.

6.5. Conclusions of the case study

While in this case study, the degradations are mild, and the degradation model is specifically for the pavement system in the Netherlands, still some clear conclusions can be made. The concept works well and brings realistic results with the chosen input. Clear interventions are not only suggested after bounds are passed as is visible in Figures 4 and 5 where no bounds are passed. Often just two maintenance options per road are chosen; the reason for this is that the mentioned maintenance options improve the condition of one degradation only. If smaller values for the bounds on the condition (or higher bounds for friction) are chosen, the overall quality of the pavement is higher, so more interventions are found and maintenance cost increases. In the case of scenario-based TIO, the costs found are similar to deterministic TIO. Usually in moving horizon optimisations, when a larger prediction window is chosen, the costs found are usually lower, but in this case study, sometimes an intervention is suggested just before the end of observation time which results in a higher cost than expected. In this paper, a prediction window of 24 months is chosen, this is both realistic and turned out the best value for optimal results. When the cost factor of degradation is increased, the found cost reduction with the optimisation method increases.

7. Discussion

While results of the case study look good, we have to keep in mind the accuracy of the found optimal strategy depends on the accuracy of the parameters used.

A way to deal with uncertainties in parameters is to find the distribution functions of these parameters, this requires further research. From the simulations done while making the case study we learned that differences in results can be found for different scenarios and parameters. Also, weather and soil behaviour and the development of traffic intensity are often not precisely known, more research may bring better predictions. Even a good prediction model of the degradation and a well-developed optimisation method cannot make regular inspections superfluous as there will be unexpected damages caused by soil movements, accidents or weather influences. Furthermore, the number of vehicles passing can be much more than expected. The pavement may not meet the agreed quality standards because of faulty fabrication, for instance, wrong binder choice, wrong compaction and bad weather during fabrication. This may result in a degradation that is different from the expected degradations.

8. Conclusions

A chance-constrained Time-Instant-Optimisation approach for predictive maintenance of asphalt-concrete pavement systems has been presented. The model used in this approach is built upon existing models from the literature and that has been adapted, so the resulting model can be used for maintenance optimisation of asphalt-concrete pavement systems. Because of the generic character of the conceptual approach in this paper, other models (for degradation and for maintenance interventions) can be easily used instead. The background for choosing every aspect within the proposed approach, such as the one-level optimisation approach, the time-instant-optimisation, the cost functions and the chance constraints, have been explained. Next, the proposed approach has been applied to a case study with Asphalt Concrete (AC) and Porous Asphalt (PA) and with representative numbers to explain and to assess the method. The cost reduction found in the case study is 4.6%, which represents substantial savings in terms of financial costs. When assessing these results, one has to keep in mind the comparison is done with the developed model, not with real results.

9. Recommendations

Recommendations for future research are

- Finding more accurate models for degradation. This includes descriptions for seasonal effects, for example, friction shows very different values in the winter, compared to the summer. Different locations may have different degradations. Furthermore, the current degradation models are found with regression techniques, while other methods, such as artificial network techniques, can bring more accurate results.
- Finding degradation models for new pavement materials. Examples are epoxy as a binder material that can result in an expected lifetime that is a lot higher than the materials used up to now and materials that result in silent pavements. If these materials find their way into the pavement system and an optimal maintenance strategy with the model, as developed in this paper is used, degradation models for these new materials have to be found.
- Including user costs. While in this article, user costs such as energy consumption and lost time, are not taken into account, it can help finding better solutions. A higher friction, for example, increases the energy consumption of vehicles but also a lower bound is vital to prevent accidents.
- Including recycling in the cost. At this moment, asphalt in the Netherlands is being recycled for more than 90%. To decide if the use of a new material is cost effective, the cost for recycling should be taken into account, as the cost for recycling is part of the maintenance costs.
- Including carbon footprint. This includes the fabrication of the components for the asphalt, the fabrication of the road and also the maintenance and use of the road.
- Compare different optimisation methods. In this paper, genetic algorithms are used, but other optimisation methods, such as water cycle algorithm, whale optimisation algorithm and particle swarm optimisation algorithm, may show even better results.

- Validation in real life. The proposed approach in the current paper can be validated on real roads to assess the method and to find more accurate parameters for the model.

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