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Decision support for tactical planning – A use case of the INFRALERT project

Ute Kandler[a]*, Axel Simroth[a], João Morgado[b], Emanuel Duarte[b]

[a] *Fraunhofer IVI, Zeunerstr. 38, 01069 Dresden, Germany*

[b] *Infraestruturas de Portugal, SA, Direção de Asset Management, Rua de Santa Apolónia, 65, 1100-468, Lisboa, Portugal*

Abstract

The final objective of the INFRALERT system is to provide Infrastructure Managers/Owners and Maintenance Operators/Contractors with intelligent software tools to support the decision-making process when planning maintenance activities and interventions. We focus on the application of INFRALERT for tactical planning in the road pilot in Portugal, where the maintenance department has to allocate major interventions over a 5-year time horizon. The tactical planning has to optimise simultaneously the maintenance intervention costs, the quality index and the availability of the network. The allocation and selection of interventions in the tactical plan is based on the maintenance alerts generated by the INFRALERT Alert Management toolkit, which is based on predicted future conditions coming from the Asset Condition toolkit. The corresponding mathematical optimisation model which reflects the uncertainty in the problem description has been developed as foundation for the decision support tool. The handling of uncertain information in the decision support tool is done by applying a scenario approach.

Keywords: Optimisation under uncertainty, Modelling, Monte-Carlo Rollout, Planning problem, Tactical planning, Multi objectives

*Tel: +49 351 4640-636
E-mail address: ute.kandler@ivi.fraunhofer.de

1. Introduction

The increasing demand and utilisation of linear infrastructure especially railway systems and road networks requires innovative methodologies to optimise the performance of the existing infrastructure. Therefore, the INFRALERT project will develop, deploy and exploit solutions to enhance the performance of linear infrastructure and adapt its capacity to meet growing needs. INFRALERT aims to develop an expert-based information system – the eIMS – to support and automate infrastructure management from measurement to maintenance. One of the final objectives is the usage of the eIMS for the decision making process in maintenance interventions planning.
In this paper we investigate the decision support on the basis of a use case regarding a road network operated and maintained by Infraestruturas de Portugal (IP), where the following issues are addressed:

- Planning requirements on the road network by the infrastructure manager
- Tactical planning for surface maintenance of the road network. Using degradation, recovery and optimisation models to support intervention plans for geometry maintenance.
- Integration of the capacity utilisation of the road network into the tactical maintenance planning
- Integration of external dependencies (i.e. weather)
- Integration of probabilistic information from uncertainties in predictions of infrastructure condition and associated model parameters.

The presented models and solution methodologies are based on previous work on maintenance planning of infrastructure systems in long, mid and short-term scenarios, see e.g. (Baldi et al., 2015, 2016; Heinicke et al., 2012, 2013, 2015; Heinicke and Simroth, 2013).

2. Problem description

For the use case of the Portuguese road network, the task of the maintenance decision-makers can be described in the following way: On a tactical planning level, which is considered as the mid-term planning, the maintenance department has to allocate major interventions over a 5-year time horizon. To avoid multiple traffic interruptions on the same section only one intervention per year and per road section is allowed. Thus the interventions are combined and aggregated as single events over 500 m-segments of certain road sections. The allocation of such intervention events is done on a monthly basis. In detail, the decisions to create a tactical plan include the following steps:

- The selection of a minimum level of intervention (to keep a certain quality limit) on a section.
- Generation of intervention events.
- The allocation of starting months for intervention events (within the next 5 years).

The inputs for tactical planning are no concrete work orders to be scheduled, but predicted work orders provided with the corresponding probabilities of occurrence. Moreover, the ending time of each intervention event will be only known at execution time, because of the uncertainty regarding the real amount of work to be done. The selection and allocation of the intervention events in the tactical plan is based on the maintenance alerts generated by the INFRALERT Alert Management tool kit. In turn the Alert Management is based on predicted future conditions coming from the INFRALERT Asset Condition tool kit. More information regarding the INFRALERT Asset Condition and Alert management tool kit can be found in (Morales et al., 2017).
The selected minimum level determines which segments of the respective road section actually have to be maintained. We choose the segments whose state would cause an alert with an intervention level equal or higher than the selected minimum at some time point during the considered time period. These characteristics make the tactical planning to an even more challenging problem with stochastic aspects, which call for specific modelling and solution techniques to be applied.
The decision-maker has to consider certain restrictions like the given yearly and overall budgets for maintenance or capacity restrictions of available equipment. The objectives of the tactical planning are to ensure a certain overall quality level of the network and to limit influence on traffic due to the closure of road sections for planned interventions, by consuming minimum costs for maintenance.

In the following we describe a mathematical optimisation model which reflects the uncertainty in the problem description. It has been developed as foundation for the INFRALERT decision support tool.

2.1 Variable declaration

We define:

- $a \in A$: Assets (segments)
- $b \in B$: Sections
- $q_a(t)$: Expected quality index for asset a at time t
- $\bar{Q}_a$: Minimum quality limit that has to be satisfied by asset a
- $T = \{1, 2, \dots, t_{\text{max}}\}$: Planning horizon with t_{max} months
- $v(G, f)$: Measure of the availability of the network G and the flow f
- $I_a = \{1, 2, \dots, K\}$: List of interventions for asset a associated with degradation levels $k = 1, 2, \dots, K$
  - c_i: Costs of intervention i
  - $d_i(t)$: Duration of intervention i in months dependent on the start month t of the intervention l (in the rain period, pavement works need more time, see Figure 1)
  - $t_i^s \in \{1, 2, \dots, t_{\text{max}}\}$: Planned starting time of intervention i
- E: List of event interventions for the planning horizon T
- $e \in E$: Event
  - c_e costs of the event intervention$e$ (are computed from the information on asset level)
  - d_e duration of the event intervention e (are computed from the information on asset level)
  - $t_e^s \in \{1, 2, \dots, t_{\text{max}}\}$ planned starting month of event intervention e
  - S_e list of assets (segments) a that are maintained by the event intervention e
  - $z(e, b)$ equals 1 if event intervention $e \in E$ belongs to the section $b \in B$ and 0 otherwise
- R: planning region
- $r \in R$: supervisor district with staff capacity n_r
- r_e: district of event e
- w_a: measure of the importance of asset a
- $p_a^k(t)$: probability that asset a is in degradation level k at time t
- P_{max}: probability limit that an intervention for asset a is not associated with a degradation level higher than the expected level k
- C_1, C_5: annual and 5-year budget with $C_5 \geq C_1 \geq \frac{C_5}{5}$
- $y_a \in I_a \cup \{0\}$: planned intervention of asset a (0 means "do nothing")

2.2 Mathematical Model

Assuming that no maintenance is executed, the distinct degradation levels represent the road condition which become worse over time. Each degradation level is linked to a certain intervention, where the different types of interventions are listened in Table 1. Each intervention l is associated with certain costs c_l and a duration $d_l(t)$.

Table 1: Maintenance types

Maintenance type	Alert	Description
TO	No	No maintenance requested
T1	Yes	Do nothing
T2	Yes	Microsurfacing, Surface dressing
T3	Yes	Thin Hot-Mix Asphalt overlay (thickness $\leq$ 5cm)
T3.1	Yes	Surface milling with Thin Hot-Mix Asphalt overlay (thickness $>$ 5cm)
T4	Yes	Thick Hot-Mix Asphalt overlay (thickness $>$ 5cm) combined or not with milling

The duration of the intervention depends on the starting month of the intervention, because pavement works can

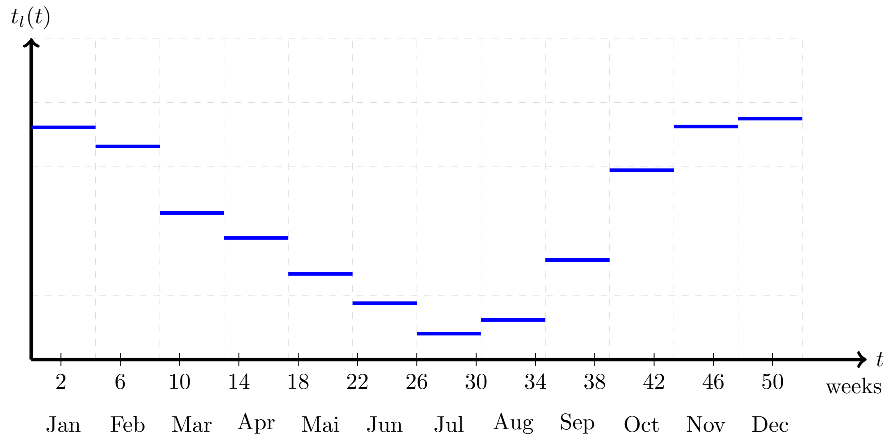

Figure 1: Duration of the invention influenced by the rain period

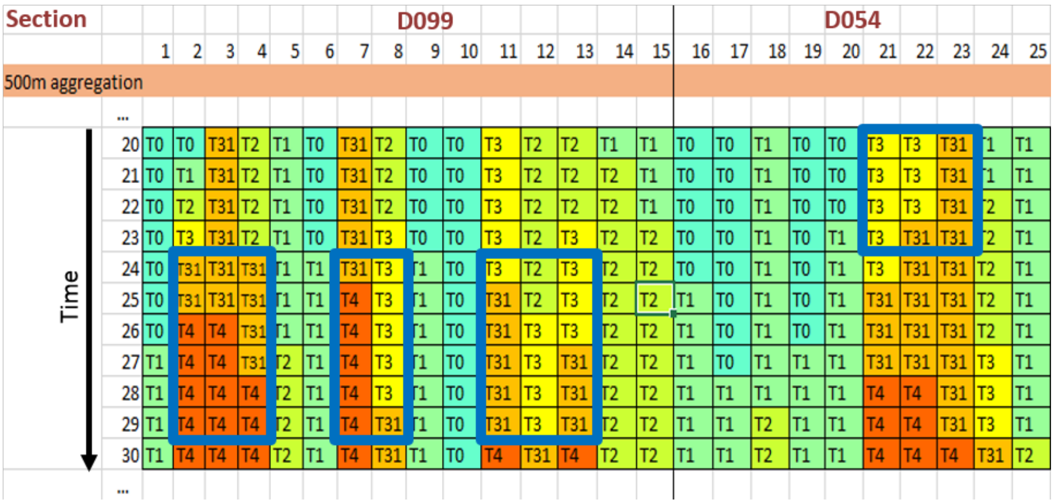

Figure 2: Example for the allocation of events

by only executed during dry weather conditions. This leads to an extension of the working duration during the rain period, see Figure 1.

Further, we want to avoid multiple interventions in the same section during the planning interval in order to have a limited traffic interruption. Therefore, we construct a new planning quantity called events. An event is an aggregation of interventions that belongs to a single section. More precisely, we set a threshold for the intervention level and investigate for each segment of this section whether the threshold is reached or exceeded during the planning period. If this is the case the corresponding intervention belongs to the event belonging to this section. An illustration of the allocation of events is provided in Figure 2, where we see the development of the degradation level of segments corresponding to the sections $D099$ and $D054$ for a time horizon of 10 months. Every segment that reaches the quality threshold of $T3.1$ belongs to the event of the section. Hence, marked by the blue square we can aggregate the corresponding events. Note that an event does not have to be connected, as you see in section $D099$. Depending on the importance of the section we can determine the quality threshold for each section separately. The limitation of the number of intervention events per district and time interval will reduce traffic interruption caused by maintenance. Note that an early intervention, i.e., in a low degradation level, is less expensive than later on in a higher degradation level. In the tactical planing we decide whether an event can be executed or has to be shifted into the next time slot. The latter case could be caused by budget constraints or restrictions on the number of interventions per week. Shifting usually implies a higher degradation level and consequently more complex and expensive intervention.

Our aim is to find a Pareto-optimal solution that optimises the maintenance costs the overall road condition and the network availability under certain restrictions. As described above there is a trade of between the costs and the overall network quality, i.e., the higher the reached degradation level is the higher are the costs and the duration of the intervention and consequently the worse becomes the network quality. The multi-objective target function, stated in (1), (2) and (3) minimises the overall costs for the planed interventions corresponding to the assets $a \in A$, maximises the average road condition and the availability of the network simultaneously.

$$\min \sum_{e \in E} \sum_{a \in S_e} c_{y_a} \tag{1}$$

$$\max \sum_{a \in A} \sum_{t=1}^{t_{\max}} q_a(t) w_a \tag{2}$$

$$\max\ v(G, f) \tag{3}$$

In equation (2) the measure w_a provides additional information about the importance of asset a. Further, during the optimisation process several restrictions have to be satisfied. The following two restrictions identify limitations on the budget.

$$\sum_{e \in E} \sum_{a \in S_e} c_{y_a} \leq C_5 \tag{4}$$

$$\sum_{e \in E} \sum_{a \in S_e : \left\lceil \frac{t^s_{y_a}}{52} \right\rceil = j} c_{y_a} \leq C_1 \qquad \forall j = 1, \ldots, 5 \quad \text{with} \quad C_1 \geq \frac{C_5}{5}. \tag{5}$$

Restriction (4) indicates that the mid-term budget for road major maintenance is not exceeded. Additionally, in (5) an annual budget limit is introduced. However, this limit is described as a "smooth" value which means that the upper bound C_1 can be seen as a point of reference rather than a strict upper limit. Thus, as long as we meet the mid-term budget, a slight exceeding of one fifth of the mid-term budget is allowed, as indicated by $C_1 \geq \frac{C_5}{5}$. Further we want to restrict perturbations of the traffic caused by interventions. This is realised by the restriction

$$\sum_{e \in E} \sum_{b \in B} z(e, b) \leq 1, \tag{6}$$

which ensures that during the planning period only one event intervention is executed per section. Since all interventions are performed with external contractors there is no limit on the number of workers on the road. However, we have to consider supervision-related restrictions, i.e.,

$$\sum_{e \in E : r_e \in r \wedge t \in \{t^s_e, \ldots, t^s_e + d_e\}} 1 \leq n_r \qquad \forall r \in R, \forall t \in T. \tag{7}$$

The condition ensures that the maximum number of event interventions running in the same month and in the same district is not exceeded, such that it is possible to supervise all working teams.

Furthermore, we have to ensure a certain quality level of the road network, which is implemented by

$$q_a(t) \geq \bar{Q}_a \qquad \forall a \in A, \forall t \in T : t \leq t^s_{y_a}. \tag{8}$$

Restriction (8) ensures that during the duration of the intervention the expected quality index for each asset a does not fall below a specific threshold $\bar{Q}_a$.

The last restriction

$$\sum_{k=y_a+1}^{K} p^k_a(t^s_{y_a}) \leq P_{\max} \qquad \forall a \in A \tag{9}$$

characterises the robustness of the model. To be more specific, the probability that an intervention for asset a is associated with a degradation level higher than the expected level k is bounded by $P_{\max}$. Thus, the probability that an intervention will be more expensive than expected is bounded from above.

2.3 Integration of the traffic

An intervention event does either lead to road closure or to a reduction of the road capacity. In order to optimise the availability of the road network we investigate in the following the optimal combination of necessary and optional intervention events. With other words, we analyse which of the intervention events can be done at the same time such that the interruption of the traffic flow is minimal. The main idea is to evaluate the traffic flow of the road network under the assumption that certain intervention events are carried out. Therefore, we compute an influence matrix that indicates the effect on the network availability for each combination of two intervention events. Based on this matrix we apply a heuristic to decide, which of the optional interventions fit best to the necessary ones.
For more details regarding the modelling and the implementation of the traffic analysis tool see (INFRALERT-Consortium, 2017).

3. A Simulation-based Solution Method

The planning problem presented above is solved by the Monte-Carlo Rollout method. This method generates a set different solutions and selects the best alternative based on an evaluation value, which results from simulated future scenarios. It combines ideas from Rollout algorithms (cf.(Bertsekas and Castañon, 1999; Bertsekas et al., 1997)) and Monte-Carlo tree search (cf. (Brügmann, 1993; Kocsis and Szepesvári, 2006; Chaslot et al., 2008)) to create robust solutions for optimisation problems under uncertainties.
The main idea is to create a set of different solutions – called alternatives – and to evaluate the behaviour of each alternative in a set of random future scenarios. Based on the evaluation of the alternatives in future scenarios, the best alternative is selected. Thereby not only the average costs caused in the random future scenarios are a criterion for the choice, but also the quality and availability of the alternatives is evaluated and considered when selecting the best solution.

3.1 The Monte-Carlo Rollout method

Based on Rollout method we evaluate the alternative solutions by solving the problem using a simple and fast base heuristic. The uncertainties are covered through the random selection of future situations, by means of a random player as in the Monte-Carlo tree search algorithm.
In more detail the optimisation problem with uncertainties is modelled as a two-player game, where the first player is the decision maker that decides on the base of a simple heuristic. The second player is the random player that creates new future situations by random. The game where both players move consecutively is called Monte-Carlo Rollout. With a set of different Monte-Carlo Rollouts, an alternative solution can be proven and evaluated in a set of random future scenarios and the long-term behaviour and robustness against uncertainties of the alternative solution could be analysed. The Monte-Carlo Rollout method is shown schematically in Figure 3.

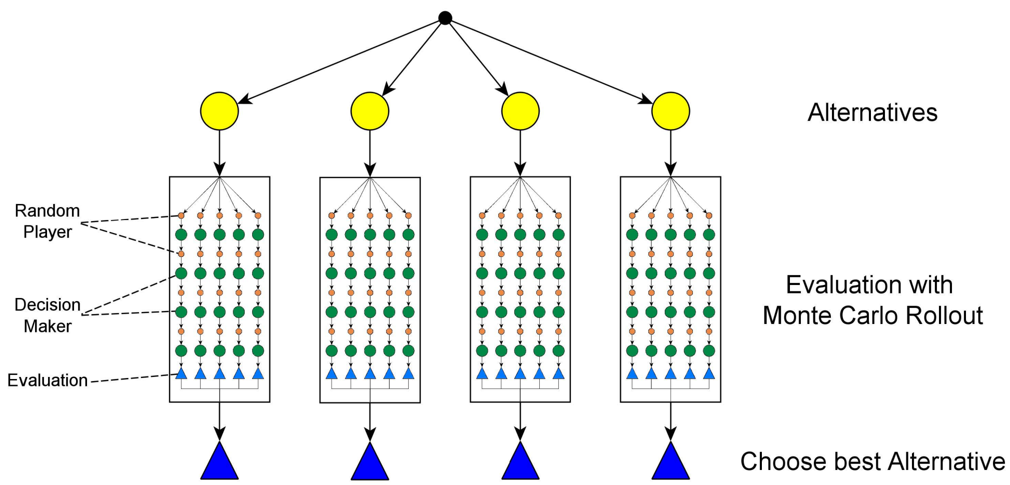

Figure 3: Schematic representation of Monte-Carlo Rollout method

3.2 Application of the Monte-Carlo Rollout Method

The generation of a tactical interventions plan using the Monte-Carlo Rollout method, can be divided into two steps: In the first step we provide a rather rough plan, i.e., we allocate the event interventions to the 5 years of the planning time horizon. In the second step we schedule the event intervention of each planning year on a monthly basis.

First Planning Step:
The starting point of this considerations are n_s different scenarios which model possible future developments of the asset conditions. Based on this we have to generate the intervention events for all possible intervention levels, sections and planning years. Thus, we take each intervention level from T1 to T4 as threshold and investigate which segments of the corresponding section reach or exceed this threshold if the intervention event is executed at time step t, where $t \in \{1, \dots, 5\}$ indicates the execution year. This procedure results into 5 intervention events per section for each time step $t \in \{1, \dots, 5\}$, i.e., we obtain a list of 5×5 intervention events per section.
To generate a plan we have to specify in the following for each section which intervention level should be applied and in which year the resulting intervention event should be executed. This problem is modelled via a bin packing problem, where each bin symbolises one year of the planning horizon. The packing of the bins is realised using a First-Fit heuristic, presented in the following section.

3.2.1 The First-Fit Heuristic

The First-Fit heuristic starts with the prioritisation of the event intervention, thus we prioritise a list E that includes all intervention events of the different sections, intervention levels and time steps, i.e., we prioritise a list of $5\times5\times n_b$ elements, where n_b is the number of sections. An event intervention should be of higher priority if we assume a rapid cost increase or a low quality in the next year. Therefore, sorting the intervention events by a non increasing priority means managing and placing the most urgent intervention events first. The priority measure consists of two components:

- The increase of the average expected costs over the of year t if the intervention event e is shifted from year t to $t+1$, which is defined by

$$\Delta c_e(t) := \sum_{i=1}^{n_s} \left(\sum_{m=1}^{12} \frac{\mathbb{E}(c_e(12t+m,i))}{12} - \sum_{m=1}^{12} \frac{\mathbb{E}(c_e(12(t-1)+m,i))}{12} \right) / n_s \qquad \forall t \in \{0, \dots, 4\}.$$

  Note that the first variable of the function c_e represents the month of the corresponding planning year, i.e., the first year t contains month 1 to 12, the second month 13 to 24 and so one. Moreover, the second variable s of the function c_e reflects the different cost evaluation for different future developments/scenarios. Note that the cost arise from the LCC analysis and are stochastic variables itself, i.e., they result from a previously executed Monte-Carlo simulation.

- The average quality if the intervention event e is executed at some point in year $t+1$, that is defined by

$$\bar{q}_e(t) = \sum_{i=1}^{n_s} \sum_{m=1}^{12} \left(\sum_{a \in e} q_a(12t+m, i) \right) / 12 n_s \qquad \forall t \in \{0, \dots, 4\}.$$

Thus, combining the last two components leads to the following priority measure of event e

$$g_e(t) := \lambda_1 \Delta c_e(t) + \lambda_2 \bar{q}_e(t), \tag{10}$$

where λ_1 and λ_2 are user dependent parameter, i.e., this parameter represent the user preferences regarding costs and quality.
In Algorithm 1 the First-Fit heuristic is described as pseudo code, where the variable x describes the computed maintenance plan. More precisely $x(e,t)$ equals one if the intervention event e is allocated in to the time slot t and zero otherwise. Further, each intervention event e depends on the corresponding time slot t, the section b and the intervention level ℓ.

Algorithm 1 First-Fit Heuristic

```
1: Generate a list of all possible intervention events E
2: Compute the priority measure g_e for all e ∈ E
3: while E nonempty do
4:     Choose event e*(t*, b*, ℓ*) with g_{e*} = max_{e∈E} g_e
5:     if Σ_{e∈E:x(e,t*)=1} c_e + c_{e*} < C_{t*} & Σ_{e∈E:x(e,t*)=1∧r_e∈r} 1 ≤ 12n_r   ∀r ∈ R   then
6:         x(e*, t*) = 1
7:         Remove all intervention events corresponding to section b* from list E
8:     else
9:         Remove intervention event e*(t*, b*, ℓ*) from list E
10:    end if
11: end while
```

We start in the first step with the generation of a list E of all possible event interventions, i.e, we build the event intervention for all segments, all interventions levels and all time steps of the planning horizon . Moreover, we compute the priority measure, as defined in equation (10), for each event intervention that belongs to the list E. We choose the event with the highest priority and allocate it into the corresponding planning year if the cost and capacity constraints are not violated. After allocating event intervention e^* we remove all other event interventions that correspond to section b^* from the list E . If the event intervention does not fit into the corresponding planning year, i.e., it violates constraints, we just remove this specific event intervention from the list and continue with Step 3 of Algorithm 1. Finally, if list E is empty we managed to construct one possible plan x.

3.2.2 Monte-Carlo Rollout method

Based on the above First-Fit Algorithm that generates on possible plan we investigate in the following the Monte-Carlo Rollout method in order to choose the plan with the best evaluation for achieving a robust and high-quality solution. The pseudo code of the Monte-Carlo Rollout method is presented in Algorithm 2, where we used the following additional notation:

- x_i: Plan where we fix the intervention event e_i and compute the resulting plan via the First-Fit heuristic.
- $\alpha_1, \alpha_2, \alpha_3$: User dependent parameters that weight costs, quality and availability of a certain plan.

The starting point is a list E that contains the intervention events for all segments, all interventions levels and all time steps of the planning horizon. Further, using (10) we compute for each intervention event the priority measure g_e and determine the section b^* that corresponds to the intervention event with the highest priority. To analyse the situation for all possible event interventions $\{e_0, e_1, \ldots, e_k\}$ that could be executed on the section b^*, we check for each $e_i \in \{e_0, e_1, \ldots, e_k\}$ whether the budget and capacity constraints in Step 7 are satisfied. If the intervention event e_i is feasible we compute the corresponding plan x_i while applying the First-Fit heuristic to the reduced set $E \setminus \{e_0, e_1, \ldots, e_k\}$. This plan x_i is evaluated, in Step 11, for n_s different scenarios, i.e., we compute a weighted sum of the costs, quality and availability for each scenario σ_j. The weights α_1, α_2 and α_3 are user dependent and represent the preferences of the user. In order to obtain an evaluation of the plan x_i we compute in Step 16 the average (arithmetic mean) of the evaluations for the different scenarios. Finally, we select from $\{e_0, e_1, \ldots, e_k\}$ the intervention event e_{max} with the highest evaluation value $\bar{f}(x_{\text{max}})$ and remove all interventions events $\{e_0, e_1, \ldots, e_k\}$ from the list E . We continue with this algorithm until the list E is empty which implies that all intervention events are allocated to the 5 planning years. Consequently, the first planning steps results into a yearly allocation of the intervention events.

Second Planning Step:
In the second step we want to refine the planning in order to get a monthly allocation of the intervention events. Therefore, we consider each planning year separately.
We start with the prioritisation of intervention events using the difference in estimated costs Δc_e, quality Δq_e and failure effects $\Delta(\mathbb{E}\,(T_{down})P_{failure})$ for month 1 and 12 of the planning year, i.e., we consider a priority measure of the form

$$h_e := \alpha_1 \Delta c_e + \alpha_2 \left(\Delta q_e + \Delta(\mathbb{E}\,(T_{down})P_{failure})\right), \tag{11}$$

Algorithm 2 Monte-Carlo Rollout

1: Generate a list of all possible intervention events $e(t, b, \ell) \in E$
2: Compute the priority measure $g_e \; \forall e \in E$
3: **while** E nonempty **do**
4: Choose m intervention events $L^* = \{e_1^*, \ldots, e_m^*\}$ with the highest priority measure
5: **for all** Intervention events $e^* \in L^*$ **do**
6: **for all** Scenarios $\sigma \in \Sigma$ **do**
7: **if** $\sum_{e \in E: x(e,t^*)=1} c_e + c_{e^*} < C_{t^*}$ & $\sum_{e \in E:(x(e,t^*)=1 \wedge r_e \in r)} 1 \leq 12 n_r \quad \forall r \in R$ **then**
8: Set $x'(e^*, t^*) = 1$
9: Determine $E' := E \setminus \{e$ that belong to section $b^*\}$
10: Compute x'_σ via applying the `First-Fit Heuristic` (Algorithm 1) to E'
11: Evaluate the plan and compute $f(x'_\sigma) := \alpha_1 c(x'_\sigma) + \alpha_2 q(x'_\sigma) + \alpha_3 v(x'_\sigma)$
12: **end if**
13: **end for**
14: Compute the average rating $\bar{f}(e^*) = \left(\sum_{\sigma \in \Sigma} f(x'_\sigma) \right) / |\Sigma|$
15: **end for**
16: Choose event $e^* = \underset{e^* \in L^*}{\text{argmin}} \, \bar{f}(e^*)$
17: $E = E'$
18: $x(e^*, t^*) = 1$
19: **end while**

where α_1 and α_2 are user dependent parameter. Via the failure effect, we add an additional component to the priority measure in order to model effects of failures which lead to short-term, operational interventions. Therefore, we use predicted RAMS parameter for failure modes based on asset condition parameters. More precisely, we us the product of the failure probability and the expected downtime due to the failure.

Based on the measure (11) we select the intervention event with the highest priority and allocate it into the first month. Further, we select from the remaining intervention events the ones that best fit to selected event, i.e., we add intervention events such that the availability of the network does not decrease more that $n\%$ and the capacity constraint in Step 7 is satisfied. This procedure is repeated for all the 12 months. The corresponding pseudo code is presented in Algorithm 3, where x_i^m describes the monthly plan of the planning year i.

Algorithm 3 Monthly allocation

1: **for all** Planning years $i \in \{1, 2, \ldots, 5\}$ **do**
2: Consider the list of intervention events E_i generated in the first step for the planning year i
3: Compute the priority measure h_e
4: **for all** Planning months $j \in \{1, 2, \ldots, 12\}$ **do**
5: Choose event intervention e^* with max h_e^*
6: $x_i^m(e^*, j) = 1$ ▷ Allocate e^* into month j
7: Choose intervention events $\{e_0, e_1, \ldots, e_k\}$ from $E_i \setminus e^*$ such that
$v(G, f)$ does not decrease more than $n\%$ and
$\sum_{e \in E_i: x_i^m(e,j)=1 \wedge r_e \in r} 1 \leq n_r \quad \forall r \in R$
8: **for all** $e_l \in \{e_0, e_1, \ldots, e_k\}$ **do**
9: $x_i^m(e_l, j) = 1$ ▷ Allocate $\{e_0, e_1, \ldots, e_k\}$ into month j
10: **end for**
11: Remove all intervention events with $x_m(e, j) = 1$ from list E_i
12: **end for**
13: **end for**

4. Conclusion

In this deliverable we considered the mathematical modelling and algorithm design for the tactical maintenance planning. Therefore, we investigated a part of the Portuguese road network and considered maintenance decisions on the tactical planning level. In particular we focused on:

- Integration of uncertain information (e.g. the ending time of each intervention event will be only known at execution time)
- Avoiding of multiple traffic interruptions
- Integration of traffic flow into the optimisation model
- Integration of seasonality (more precisely weather dependency)
- Using stochastic information

In general we focused on the definition on the mathematical optimisation model, involving the objective functions, degree of freedom and restrictions, where the objective functions are linked to the evaluation framework and KPI's. In the algorithm design phase we applied the Monte-Carlo Rollout method to take into account the uncertain and stochastic information of the use case.

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