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Report on models and algorithms for decision support

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Executive Summary

INFRALERT aims to develop an expert-based information system to support and automate infrastructure management from measurement to maintenance. This report describes two use cases. In the first use case we consider a road network maintained by Infraestruturas de Portugal (IP), where we investigate the tactical planning process. The second use case analyses the operational planning phase of a Swedish railway infrastructure maintained by Trafikverket (TrV). In both use cases we illustrate the deployment and implementation of solutions, models and methodologies that will be developed within the project.

This report provides some insights into maintenance planning procedure, objectives and limitations within the planning process. This is expected to facilitate the acceptance and application of the resulting methods and tools by rail and road Infrastructure managers. The use case covers tactical and operation planning aspects that are addressed within the project. Further aspects covered are probabilistic information associated with infrastructure conditions, alerts for enhancing the robustness of maintenance schedules and integration of factors effecting the capacity of the network.

The work of WP6 will continue across the whole project's life to guarantee the necessary level of integration. To this end D6.2 will serve a repository for all the changes that will occur during the project and as reference for the final validation thus becoming a live document updated regularly whenever needed.

Table of Content

Executive Summary 4
Table of Content 6
List of Tables 8
List of Figures 9
List of Acronyms 10
1 Background 11
2 Mathematical model 12
2.1 The road use case 12
2.1.1 Variable declaration 13
2.1.2 Mathematical model 14
2.1.3 Integration of the traffic 17
2.2 The rail use case 22
2.2.1 Tactical Planning 23
2.2.1.1 Variable declaration 23
2.2.1.2 Mathematical model 25
2.2.2 Dynamic Planning 26
2.2.2.1 Variable declaration 27
2.2.2.2 Mathematical model 27
2.3 Alignment between output from WP4 and input for WP6 29
2.3.1 Variant 1: AG via fixed rules using feature levels 29
2.3.2 Variant 2: AG via learning from historical intervention records 30
3 Optimisation Algorithms 31
3.1 Input Data 31

3.1.1 Road Use case 31
3.1.2 Rail use case 41
3.2 A Simulation-based Solution Method 45
3.2.1 Rollout Algorithms 46
3.2.2 Monte-Carlo tree search 47
3.2.3 The Monte-Carlo Rollout method 47
3.2.4 Application of the Monte-Carlo Rollout Method 48
3.2.4.1 First Planning Step 49
3.2.4.1.1 The First-Fit Heuristic 49
3.2.4.1.2 Monte-Carlo Rollout method 50
3.2.4.2 Second Planning Step 52
4 Conclusion and Outlook 53

List of Tables

2 Definition knots . . . 32

3 Definition edges (sections) . . . 32

4 Current status of the asset (segment) . . . 33

5 Capacity of the supervisory staff per region . . . 33

6 OD pairs: Demand for the origin-destination pairs . . . 33

7 Definition of the interventions (depending on the moth of execution) . . . 34

8 List of interventions (planning year) . . . 34

9 Current and initial feature values . . . 35

10 Current status of the asset . . . 36

11 Status of the asset after the intervention T1 . . . 37

12 Status of the asset after the intervention T2 . . . 37

13 Status of the asset after the intervention T3 . . . 38

14 Status of the asset after the intervention T3.1 . . . 38

15 Status of the asset after the intervention T4 . . . 39

16 Influence matrix . . . 39

17 Tactical plan . . . 40

18 Assets rail network . . . 41

19 Possession time . . . 42

20 Tactical plan . . . 42

21 Train free periods . . . 42

22 List of interventions . . . 43

23 Costs of intervention . . . 43

24 Mean time to repair (MTTR) . . . 43

25 Failure probability 44
26 Downtime 44
27 Result of the short term planning 45

List of Figures

1 Duration of the invention influenced by the rain period 14
2 Example for the allocation of events 15
3 Graph of the example 20
4 Influence matrix 21
5 Dependency matrix 21
6 Maintenance and traffic planning at Trafikverket 22
7 Time horizon of the tactical plan 25
8 Flowchart 31
9 Example network 32
10 Flowchart road use case 41
11 Flowchart rail use case 45
12 Schematic representation of the Rollout approach 46
13 Schematic representation of Monte-Carlo Rollout method 48

List of Acronyms

eIMS	Expert-based Infrastructure Management System
LCC	Life Cycle Cost
RAMS	Reliability, Availability, Maintainability and Safety
WP	Work Package
OD	Origin Destination
MTTR	Mean Time To Repair

1 Background

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. For this reason, INFRALERT project will develop, deploy and exploit solutions to enhance the performance of linear infrastructure and adapt its capacity to meet growing needs. Among the few focus areas is the aspect of increasing the availability of existing infrastructure by optimising tactical and operational maintenance interventions and assessing strategic long-term decisions. In connection to the above concern and focus area, INFRALERT aims to develop an expert-based information system to support and automate infrastructure management from measurement to maintenance. The project will develop methods and tools that can be directly applied by Rail and Road Infrastructure Managers in the field of Intelligent Maintenance and long-term strategic planning and analysis of inspection data, the determination of maintenance tasks necessary to keep the performance of the infrastructure system in optimal condition, and the optimal planning of interventions. In order to reach this goal the specific technical objective below must be accomplished: "Testing, implementing and exploiting the eIMS and Data Farm in two real environments and covering two transport systems: a road and a rail network".

Therefore, this report will give a description of the road and rail use case and some specific information that will be required in the maintenance decision support modelling and demonstration. The issues addressed include:

- Planning requirements on the selected use case area 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 utilization of the road network into the tactical maintenance planning
- Model for the integration of a two-level nested planning process: mid-term (tactical) planning using predictive maintenance activities and short-term (dynamic) planning for corrective activities.
- 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. [1, 2, 3, 4, 5, 6].

2 Mathematical model

2.1 The road use case

For 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 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 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. This intervention event aggregation step is done to avoid multiple traffic interruptions on the same segment.

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. The selection and allocation of the intervention events in the tactical plan is based on the maintenance alerts generated by the Alert Management tool kit in WP4. In turn the Alert management is based on predicted future conditions coming from the Asset Condition tool kit in WP3. Thus, 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. 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.

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 decision support tool.

2.1.1 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
- $T = \{1, 2, \ldots, t_{\text{max}}\}$: Planning horizon with t_{max} months
- $v(G, f)$: Measure of the availability of the network G and the flow f
- $I_a = \{1, 2, \ldots, K\}$: List of interventions for asset a associated with degradation levels $k = 1, 2, \ldots, K$
  - 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)
  - $t_i^s \in \{1, 2, \ldots, t_{\text{max}}\}$: 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)
  - $t_e^s \in \{1, 2, \ldots, t_{\text{max}}\}$ 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”)

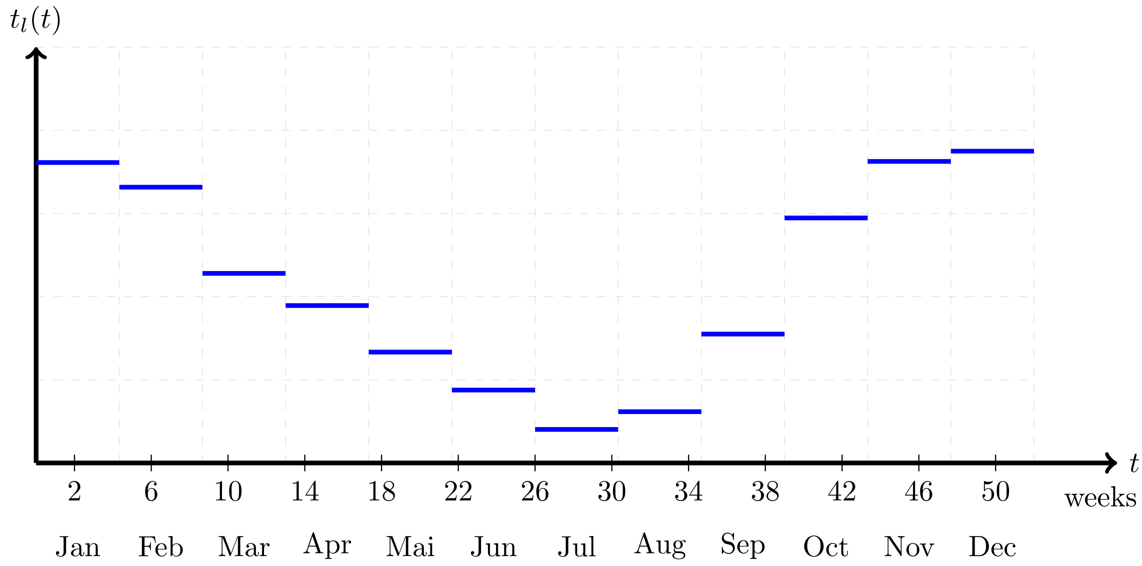

Figure 1: Duration of the invention influenced by the rain period

2.1.2 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, in doing so each intervention l is associated with certain costs c_l and a duration $d_l(t)$. The duration of the intervention depends on the month when the intervention starts, because pavement works can 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

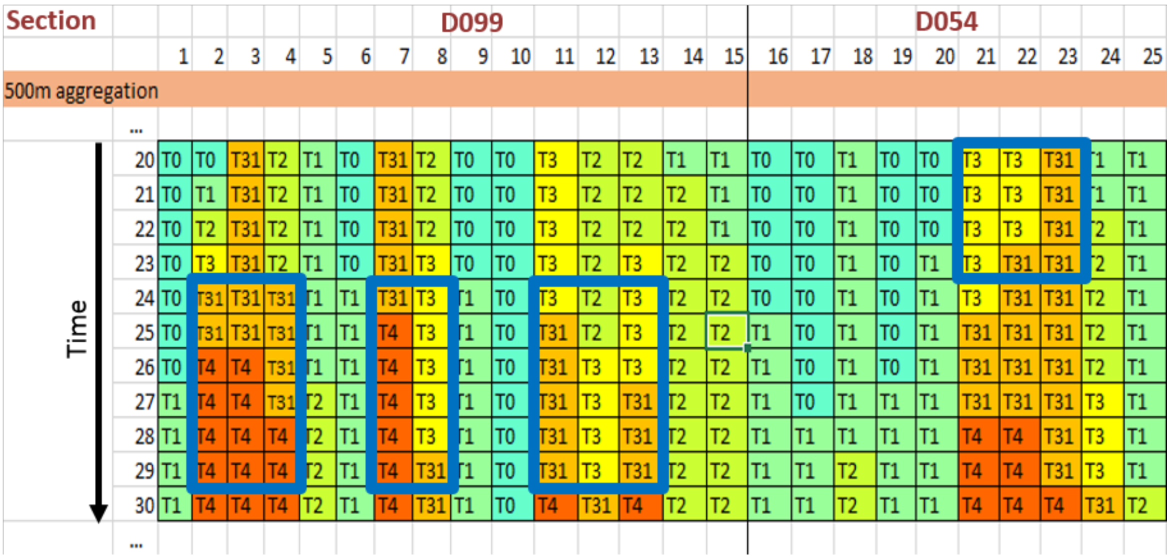

Figure 2: Example for the allocation of events

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 optimizes 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.

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

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

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

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.

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

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

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.,

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

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

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

characterizes 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.

2.1.3 Integration of the traffic

An intervention event does either lead to street 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. For this we introduce the following notation (note that this notation is only consistent within this subsection):

- $n \in N$: Nodes
- $e \in E$: Edge
- $G(N, E)$: Graph describing the road network with set of nodes N and set of edges E
- c_e: Capacity of edge e
- Ω: Set of OD-pairs
- Ψ_p: Set of routes for OD-pair p, every route r is a subset of E
- d_p: Demand of OD-pair $p \in \Omega$
- c_r: Capacity of route r
- R: Matrix, where element R_{ep} indicates how much capacity pair p reserves on edge e
- F: Matrix, where element F_{ep} is the factor that indicates how much of the capacity of edge e OD-pair p can use
- f: Vector, where element f_e is the flow of edge e
- $I = \{0, \dots, m\}$ set of possible interventions, where 0 means no intervention
- $v(G, f)$: Availability measure of a network G for a flow f
- M: Influence matrix, where element M_{ij} is $v(G, f)$ when interventions i and j are realized at the same time
- D: Dependency matrix, element D_{ij} indicates how much $v(G, f)$ changes, if interventions i and j are realized to the case where only j is realized

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.

We start with the calculation of the traffic flow for a given network. First, we compute for each OD-pair a set of routes with a sufficient capacity to satisfy the corresponding demand of the OD-pairs. Second, the flow of each edge is analysed and we identify whether an edge is used by two or even more pairs. If this is the case the capacity of the corresponding edge needs to be splitted. The splitting depends on absolute demand and to what they reserved on the edge, see line 17 of Algorithm 1. If the capacity needs to be splitted the algorithm restarts, ie., it computes routes with sufficient capacities for the OD-pairs.

Note that the computation of the network flow has to be done several times. Therefore, the following algorithm computes the network flow approximately, which is very fast and sufficiently precise for the following computations. The pseudo code is stated in Algorithm 1.

Algorithm 1 Computation of the network flow

```
1:  Input: Network G with edge capacities c_e, set of OD-pairs Ω
2:  Output: Network flow f
3:  F = 1
4:  repeat
5:      R = 0; f = 0
6:      for all p ∈ Ω do
7:          calculate Ψ_p s.t. ∑_{r∈Ψ_p} c_r = d_p with c_r ≤ min_{e∈r}(c_e · F_ep)    ▷ using Dijkstra algorithm
8:          for all r ∈ Ψ_p do
9:              for all e ∈ r do
10:                 R_ep += c_r
11:                 f_e += c_r
12:             end for
13:         end for
14:     end for
15:     for all e ∈ E do
16:         if f_e > c_e then                                                        ▷ capacity of the edge is exceeded
17:             F_ep = (d_p · R_ep) / (∑_{p∈Ω} d_p · R_ep)
18:         end if
19:     end for
20: until F didn't change
21: return f
```

In the following we want to evaluate the computed flow f for a given network G, i.e., we want to analyse the availability of the network. Therefore, we compute the auxiliary value

$$v^*(G, f) = \sum_{e \in E} \left(\frac{f_e^2}{c_e} \right)^2$$

This function is based on the workloads f_e/c_e of the edges, but they are weighted by the flow to higher the importance of bigger streets. These values are squared to rate a single huge traffic jam higher than some small ones. Finally, we sum up over all edges belonging to the network and normalise the

availability measure in order to get a more intuitive evaluation, i.e,

$$v(G, f) = \sqrt[4]{\frac{v^*(G, f)}{\sum\limits_{e \in E} c_e^2}}.$$

By ”more intuitive” we mean that the availability measure $v(G, f)$ is one if the network flow is equal to the capacity on every edge and two if the network flow is twice the capacity.

Based on the availability evaluation for certain capacities of the edges we analyse in the following the availability of the network if certain intervention events are executed. Therefore, we compute in Algorithm 2 the influence and the dependency matrix of the network and set of intervention events. To obtain the influence matrix we have to compute the availability of the network for each combination of intervention events, i.e., we apply Algorithm 1 to all possible pairs of intervention events. Further, the dependency matrix stores the difference between availability of the network if two intervention events are executed and the availability if only one of them is applied. The dependency matrix is used to compute the availability of the network for more than two intervention events. In more detail, we multiply these values we get an estimate for the evaluation with three or more interventions.

Algorithm 2 Computation of the influence and dependency matrix

```
Input: network G with edge capacities c_e, set of OD-pairs Ω, set of interventions I
Output: influence matrix M, dependency matrix D
for all i ∈ I do
    for all j ∈ I \ {i} do
        change capacity of the involved edges
        compute f using Algorithm 1
        M_ij = v(G, f)                          ▷ calculate influence matrix M
    end for
end for
for all i ∈ I \ {0} do
    for all j ∈ I \ {0, i} do
        D_ij = M_ij / M_j0                      ▷ calculate dependency matrix D
    end for
end for
return M, D
```

The prediction Algorithm takes a set of interventions I as input. Some of them, i.e., $J \subset I$, are fixed and have to be done at a certain time point, where the remaining ones can be shifted. Thus, we have to analyse which of the remaining interventions fits best to the already planned ones, which is done by the prediction algorithm, stated in Algorithm 3.

The following heuristic can be directly used to estimate $v(G, f)$, if more than two interventions have to be applied. If we want to execute interventions a, b, c, d, we first have to order them. One possibility is to order the intervention events by their impact to the network flow, which can be measured by, e.g., the sum or product of the values in the corresponding row of the dependency matrix D.

Algorithm 3 Prediction algorithm

1: **Input:** dependency matrix D, sets of interventions I and J with $J \subset I$
2: **for all** $i \in I \setminus (J \cup \{0\})$ **do**
3: $\quad X_i = 1$
4: $\quad$ **for all** $j \in J$ **do**
5: $\qquad X_i = X_i \cdot D_{ij}$
6: $\quad$ **end for**
7: **end forreturn** arg $\min_{i \in I \setminus (J \cup \{0\})} X_i$

Assuming the order a, b, c, d we compute the availability of the network by taking the entry of the influence matrix M_{ab} related the first two intervention events and include the dependency of the other intervention events by multiplying this entry with the corresponding values of the dependency matrix, i.e., the estimated availability of the network can be computed by

$$v(G, f) \approx M_{ab} \cdot D_{ca} \cdot D_{cb} \cdot D_{da} \cdot D_{db} \cdot D_{dc}.$$

Note that this measure depend on the choice of order.

Example:

We provide in the following a small example to illustrate the procedure presented before. The example network contains five nodes $K1, \ldots, K5$ that are connected by seven edges as illustrated in Figure 3, where also the capacities of the edges are provided. Further, we take into account two OD-pairs, where the first on describes the connection from node $K1$ to node $K4$ and the second one from node $K1$ to node $K5$. The demand amounts to 20 for each OD-pair.

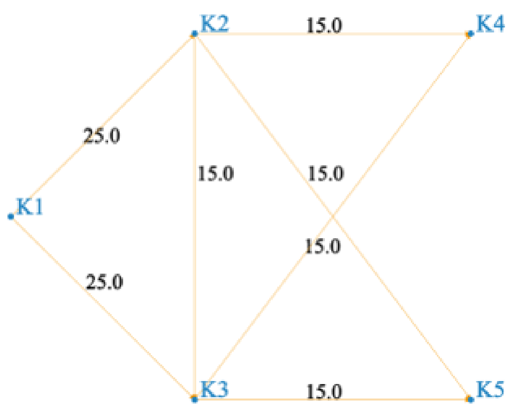

Figure 3: Graph of the example

The application of an intervention event implies a capacity reduction of 50% for the corresponding edge. With these informations we are able to compute the influence matrix via Algorithm 2, where

the result is show in Figure 4. For the evaluation of the matrix we clustered the availability measures into five categories. We coloured the categories by dark red, red, orange, yellow and green. Here green indicates a good traffic flow and red an a lot of traffic congestions. We see that if no intervention event is applied the availability measure of the network results to 0.8, thus a good traffic flow for the network is guaranteed in case of no interventions.

intervention	1→2	1→3	2→3	2→4	2→5	3→4	3→5	no int.
1→2	-	1.59	0.94	0.93	0.94	1.01	1.11	0.94
1→3	1.59	-	0.94	0.92	0.95	0.94	0.93	0.94
2→3	0.94	0.94	-	0.81	0.80	0.85	0.80	0.80
2→4	0.93	0.92	0.81	-	0.82	1.02	0.77	0.81
2→5	0.94	0.95	0.80	0.82	-	0.80	1.02	0.80
3→4	1.01	0.94	0.85	1.02	0.80	-	0.85	0.80
3→5	1.11	0.93	0.80	0.77	1.02	0.85	-	0.85
no int.	0.94	0.94	0.80	0.81	0.80	0.80	0.85	0.80

Figure 4: Influence matrix

Figure 5 shows the dependency matrix. The values there are the relative change of the availability, e.g., edge $K2 \to K3$ is never used, thus an intervention event on this edge does not change the flow and therefore the availability of the network, see the third row in the dependency matrix.

intervention	1→2	1→3	2→3	2→4	2→5	3→4	3→5	Σ
1→2	-	1.69	1.18	1.14	1.18	1.26	1.31	7.76
1→3	1.69	-	1.18	1.13	1.18	1.17	1.09	7.44
2→3	1.00	1.00	-	1.00	1.00	1.00	1.00	6.00
2→4	0.99	0.98	1.02	-	1.02	1.27	0.91	6.19
2→5	1.00	1.01	1.00	1.01	-	1.00	1.20	6.22
3→4	1.07	1.00	1.00	1.26	1.00	-	1.00	6.33
3→5	1.18	0.99	1.06	0.95	1.27	1.06	-	6.51

Figure 5: Dependency matrix

Now we want to plan three interventions events:

- intervention a on edge $K1 \to K2$
- intervention b on edge $K2 \to K4$
- intervention c on edge $K2 \to K5$

We order them by impact to the network flow (see the last column in the dependency matrix). This results to the order acb and thus we get the estimate

$$v(G, f) \approx 0.94 \cdot 0.99 \cdot 1.02 \approx 0.95$$

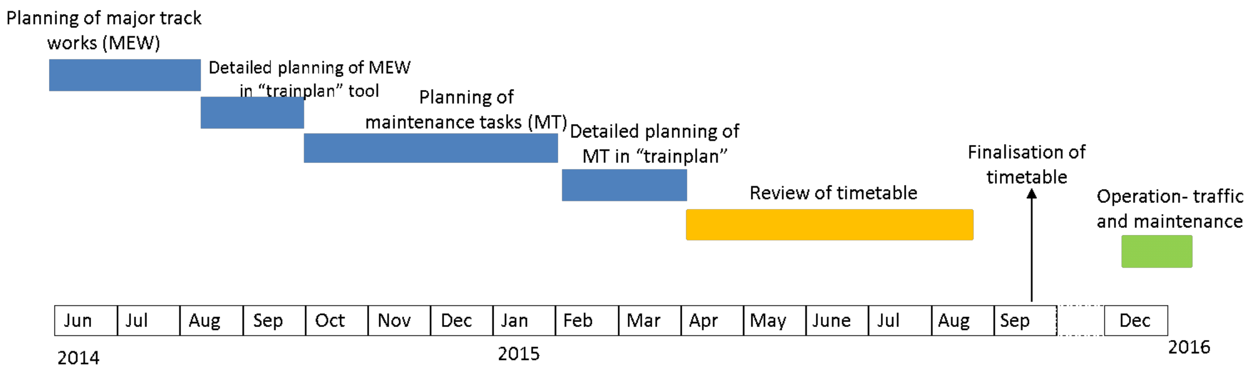

Figure 6: Maintenance and traffic planning at Trafikverket

2.2 The rail use case

The planning of railway infrastructure maintenance works is a complex task that requires good understanding of infrastructure component degradation and failure behaviour.

The general planning procedure in TrV is summarised in Figure 6. The planning for maintenance is done simultaneously with the planning for traffic and it starts at least 18 months before the implementation year. In Sweden, first, the plans for major engineering works are developed so that they could be included in the infrastructure Network Statement. The aim of the Network Statement is to provide infrastructure information, principles governing the right to operate traffic, regulations governing applications for capacity and fees related to operation of traffic. This is completed one year before the annual schedule is fixed. The planning for maintenance task starts at least 14 months before the execution date. The maintenance plan is developed using some expert knowledge together with condition information like rail profile, damage or defect history, track geometry record. The developed maintenance plan and train path request from traffic operators are the basis for the possession planning tool "train plan" for identification and resolution of conflicts. Disruptions of the requested train paths by maintenance plan has to be negotiated with train operators in the review process. The plan includes all activities except snow clearance and routine or urgent repairs tasks. The planned traffic operations and maintenance tasks are finally established in a timetable and fixed for operation about three month before the execution year starts. It is essential to mention that this plan is updated with recent condition information from inspection, failure and maintenance reports. The dynamic update is based on criticality assessment of the state of the asset and assurance of safe traffic operation. No optimisation model is reported to be in use for this purpose.

The maintenance tasks to be planned range from large engineering works, i.e., renewals, small corrective actions. The major concern of the IM is condition assessment and maintenance need analysis, which include the following activities:

- Quality/state monitoring and Long (mid) term quality prediction

- Task identification and definition
- Task prioritisation and selection
- Task merging, scheduling and resource allocation

It is important to mention that the above tasks are carried out to answer some of the main questions of maintenance planning. These include:

- What task to carry out? (Identification of tasks to carried: Based on asset records, failure records, condition records, experience and other requests)
- When to carry out the tasks?
- How to carry out the tasks?
- Who to carry out the tasks?

2.2.1 Tactical Planning

We would like to combine the tactical and dynamic planning. To be more specific, on the one hand we want to combine corrective (short time scale) maintenance tasks with interventions from of the tactical plan (long time scale), i.e., if the line is closed because of major maintenance activities which corrective maintenance tasks can be rescheduled into this train free period. On the other hand, we want to adapt the tactical plan to the dynamic plan, i.e., we want to prepone tamping actions (from the tactical planning horizon) to combine them with urgent corrective maintenance. The resulting free track possession could be used for other maintenance activities or sold back to the train operator infrastructure manager.

2.2.1.1 Variable declaration

We define:

- $T = \{1, 2, \ldots, t_{\text{max}}\}$: planning horizon of the tactical plan with t_{max} weeks
- S: considered section of the track
- $\sigma \in S$ signalling segment of the section
- C_1 annual budget
- $[w_j^1, w_j^2] = \{t \in T | w_j^1 \leq t \leq w_j^2\}$ for $j = \{1, \ldots, W\}$: possession windows

- c_j^w: booking costs of the possession window w_j
- $r_j^w(t)$: refund in case of unused possession window w_j defined in (10)
- $a \in A$: assets
- $M_a := \{\tau_1, \tau_2, \dots, \tau_m\}$: list of possible types of interventions for asset a
- $q_{a,\tau}(t)$: expected quality index for type $\tau \in M_a$ of asset a at time t
- $q_a(t) := \sum_{\tau \in M_a} q_{a,\tau}(t)$: expected quality index for asset a at time t
- $\bar{Q}_a$: minimum quality limit that has to be satisfied by asset a
- $I_{a,\tau} = \{1, 2, \dots, K\}$: list of interventions of type $\tau \in M_a$ of asset a. Each intervention corresponds to a specific degradation level $k \in \{1, 2, \dots, K\}$ reflecting the extensiveness of intervention τ for asset a
  - σ_k: signalling segment affected by intervention k
  - c_k: costs of intervention k
  - $t_k^1 \in T$: planned starting time of intervention k
  - $d_k(t)$: duration of intervention k in weeks dependent on the start week t of the intervention
  - $[t_k^1, t_k^2]$: planned time slot for intervention k with $t_k^2 := t_k^1 + d_k(t)$. We assume that it exists a j such that $[t_k^1, t_k^2] \subseteq [w_j^1, w_j^2]$
  - l_k: latest starting point (deadline) of intervention k
- w_a: measure of the importance of asset a
- $z_{a,\tau}(t) : \mathbb{R}^+ \to \mathbb{R}^+$ degradation function for type τ of asset a
- P_{max}: probability limit that an intervention for type τ of asset a is not associated with a degradation level higher than the expected level k
- $y_{a,\tau} \in I_{a,\tau} \cup \{0\}$: planned intervention of asset a and type τ_i (0 means "do nothing")

The maintenance process of a railway network is quite complex. For each asset $a \in A$ we consider multiple types of interventions $\tau_i \in M_a$, e.g., tamping, grinding and welding. In the tactical planning phase we have to book the long term possession times. We assume that the tactical plan for the time interval T, that equals 52 weeks and is illustrated by the orange arrow in Figure 7, is fixed in week 66. However, during the realization the tactical plan is updated four times. We can see in Figure 7 that we can update in week 78 the time sections II, III and IV, in week 91 the time sections III and IV and so forth. If it happens that an possession window is unused we can sell it back to traffic. The relative

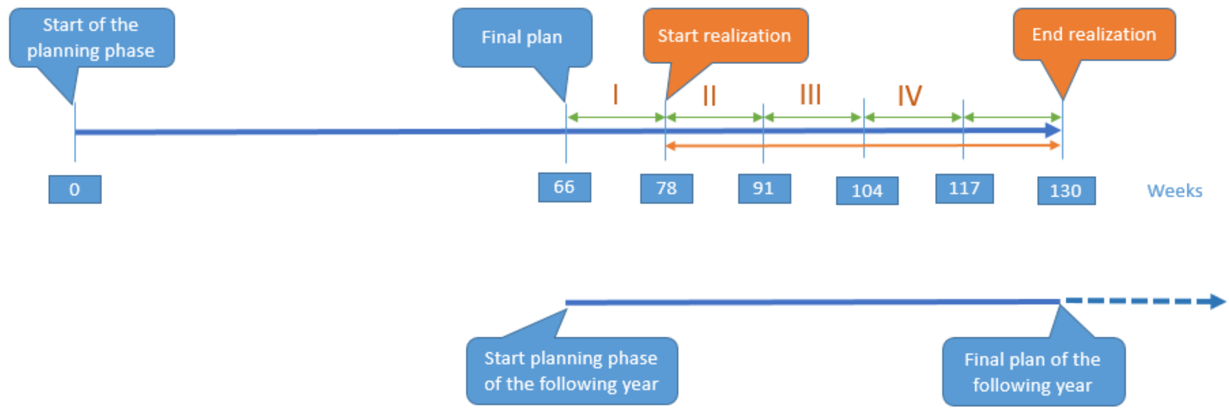

Figure 7: Time horizon of the tactical plan

refund is defined by

$$r_j^w(t) = \begin{cases} 0.75 & \text{if} \quad w_j^1 - t > 52 \\ 0.5 & \text{if} \quad 52 \geq w_j^1 - t > 39 \\ 0.25 & \text{if} \quad 39 \geq w_j^1 - t > 26 \\ 0 & \text{else.} \end{cases} \tag{10}$$

The relative refund function $r_j^w(t)$ of the possession window $[w_j^1, w_j^2]$ depends on time of sale t and on the dates where the tactical plan is updated, i.e., in equation (10) we consider the case where this is done four times a year.

2.2.1.2 Mathematical model

We aim to find a Pareto-optimal solution that optimises the costs and the overall network quality under certain restrictions. The multi-objective target function

$$\min \left(\sum_{j=1}^{W} \left(1 - r_j^w(t)\right) c_j^w + \sum_{a \in A} \sum_{\tau \in M_a} c_{y_{a,\tau}} \right) \qquad \text{overall costs} \tag{11}$$

$$\max \sum_{a \in A} \sum_{t=1}^{t_{\text{max}}} q_a(t) w_a \qquad \text{average quality index} \tag{12}$$

simultaneously minimise the costs for planed interventions and maximise the network quality for the considered time horizon. The target function regarding the costs consist of costs for booking of possession time and costs for planned interventions. The first summand of (11) describes the costs for possession time, where a possible refund in case of unused possession time is included via the function (10). The second summand of (11) describes the costs for all planed interventions, i.e., for all assets all different types of necessary interventions are taken into account. Furthermore, the

maximisation of the network quality in the considered time horizon T is described by (12), where the importance of an asset for the whole network is modeled by the measure w_a.

The optimisation process takes place under certain restrictions that result from safety regulations and a limited availability of budget, workers and equipment. We start by considering the budget constraint, i.e., we are not allowed to exceed the annual budget C_1 which is modeled via

$$\sum_{j=1}^{W} \left(1 - r_j^w(t)\right) c_j^w + \sum_{a \in A} \sum_{\tau \in M_a} c_{y_{a,\tau}} \leq C_1. \tag{13}$$

Furthermore, we have to ensure that each intervention does start before a specific deadline $l_{y_{a,\tau}}$, i.e.,

$$t^1_{y_{a,\tau}} \leq l_{y_{a,\tau}} \qquad \forall a \in A, \forall \tau \in M_a. \tag{14}$$

This restriction prevents the network from running into predictable failures. Moreover, in order to keep a certain quality limit of the network we have to ensure that

$$q_a(t) \geq \bar{Q}_a \qquad \forall a \in A, \forall t \in T : t \leq t^1_{y_{a,\tau}}. \tag{15}$$

Thus, before the planned intervention is executed the quality index of each asset is not allowed to fall under a specific threshold $\bar{Q}_a$. Additionally, it is requested by safety regulations that at the same time we do not execute two or more interventions in one signalling section. This is modelled by

$$\sum_{a \in A, \tau \in M_a : \sigma_{y_{a,\tau}} \in \sigma \wedge t^1_{y_{a,\tau}} \in D_{y_{a,\tau}}(t)} 1 = 1 \qquad \forall \sigma \in S, \forall t \in T, \tag{16}$$

with $D_{y_{a,\tau}}(t) := \{t - d_{y_{a,\tau}}(t^1_{y_{a,\tau}}), \ldots, t\}$, thus we ensure that during the duration of an intervention, i.e., during $D_{y_{a,\tau}}(t)$, only one intervention is executed in one signalling section σ. Finally, the maintenance plan has to satisfy a certain robustness level. In more detail, we request that at the time point $x_{y_{a,\tau}}$ when the intervention should be executed, the probability that the degradation for type τ of asset a is higher than an expected degradation level k is bounded from above by P_{max}, i.e., we request that

$$p\left(z_{a,\tau}(x_{y_{a,\tau}}) > k\right) \leq P_{\text{max}} \qquad \forall a \in A, \forall \tau \in M_a. \tag{17}$$

This condition also implies that the probability that an intervention will be more expensive than expected is also bounded from above.

2.2.2 Dynamic Planning

In addition to the above combined model for tactical and dynamic planning we describe in this section a simplified version covering only the short-term aspect of the planning. This simplified version is necessary to ensure the transferability of the developed decision support tools to similar situations with different, limited data availability.

2.2.2.1 Variable declaration

We define:

- $t \in T = \{1, 2\}$: planned week in the planning horizon T of the dynamic plan
- $[f_j^1, f_j^2]$ for $j = 1, \ldots, k_D^f$: train free periods
- $[v_j^1, v_j^2]$ for $j = 1, \ldots, k_D^v$: possession time (resulting from the tactical plan)
- I_t^D: list of interventions i for $i = 1, \ldots, N_t^D$ that should be executed in planning week t
  - $a_i \in A$: asset corresponding to intervention i
  - s_i: signaling section affected by intervention i
  - m_i: failure mode of intervention i
  - z_i: action to be executed by intervention i
  - $x_{i,t} := \begin{cases} 1 & \text{if intervention } i \text{ is executed in week } t \\ 0 & \text{else} \end{cases}$
  - γ_{z_i}: random variable representing the costs of the intervention i depending on the action that corresponds to i
  - ϱ_{m_i}: random variable of the repair time depending on the failure mode of intervention i
  - δ_{m_i}: random variable of the down time depending on the failure mode of intervention i
  - $p_{m_i,t}$: failure probability at week t
  - g_{z_i}: penalty costs if intervention i needs to be shifted into week two
- C_t: budget restriction of week t
- R_t: thresholds for the minimal reliability in week t

2.2.2.2 Mathematical model

In the simplified model we aim to find a Pareto-optimal solution that optimizes the costs and reliability of a network under certain restrictions. Further, the costs of interventions, the mean times to repair and the down times are not provided by concrete values but by corresponding distribution functions. This probabilistic data results from the RAMS analysis, which is considered in work package 5. Thus, we incorporate uncertain information and try simultaneously to minimize the expected costs for planed interventions and maximize the reliability of a network for a predetermined time horizon. The corresponding multi-objective target function is defined by

$$\text{min} \left(\sum_{i \in I_{t-1}^D} (1 - x_{i,t-1}) \mathbb{E}(\gamma_{z_i}) + \sum_{i \in I_t^D} (x_{t,i} \mathbb{E}(\gamma_{z_i}) + (1 - x_{i,t}) g_{z_i}) \right) \quad \text{and} \tag{18}$$

$$\text{min} \sum_{i \in I_t^D} (x_{i,t} p_{m_i,t} \left(\mathbb{E}(\varrho_{m_i}) + \mathbb{E}(\delta_{m_i}) \right) + (1 - x_{i,t}) p_{m_i,t+1} \left(\mathbb{E}(\varrho_{m_i}) + \mathbb{E}(\delta_{m_i}) \right)) . \tag{19}$$

In the target function (18) we sum over all planned interventions that should be execute in planning week t. In more detail the first summand represents the expected costs of the interventions shifted from week $t-1$ into week t. The second summand reflects the expected costs that are planned to be executed in week t and the penalty costs if an intervention from week t needs to be shifted into the next week $t+1$. Thus, we want to minimize the expected overall costs for the interventions that should be executed in the planning week t.

Further, we want to maximize the reliability of the network. This is done by the second target function (19), where we minimize the time of non-availability of the asset if a failure occurs. In more detail, we minimize the time span from the occurrence of failure until the time point where the asset is back into operation. In (19) this is modeled by adding the expected mean time to repair and expected down time of the intervention i and multiplying this sum with the corresponding failure probability. This probability depends on the week of execution of the intervention, i.e., shifting an intervention into the next week might cause a higher failure probability.

Additionally, during the optimization process we have to satisfy several restrictions. The first one describes the limitation of the weekly budget during the planning horizon. Thus we have to satisfy the restriction

$$\sum_{i \in I_{t-1}^D} (1 - x_{i,t-1})\mathbb{E}(\gamma_{z_i}) + \sum_{i \in I_t^D} (x_{t,i}\mathbb{E}(\gamma_{z_i}) + (1 - x_{i,t})g_{z_i}) \le C_t, \qquad \forall t \in T, \tag{20}$$

which implies that expected costs occurring during week t are not allowed to exceed an upper bound C_t. Further, we have to ensure that the reliability of the network may not fall below a certain level during the planning horizon. This is modeled via the following restriction

$$\sum_{i \in I_t^D} (x_{i,t}p_{m_i,t}\left(\mathbb{E}(\varrho_{m_i}) + \mathbb{E}(\delta_{m_i})\right) + (1 - x_{i,t})p_{m_i,t+1}\left(\mathbb{E}(\varrho_{m_i}) + \mathbb{E}(\delta_{m_i})\right)) \le R_t, \qquad \forall t \in T. \tag{21}$$

Hence, for all the interventions that should be analyzed in week t we sum over the expected time of non-availability $(\mathbb{E}(\varrho_{m_i}) + \mathbb{E}(\delta_{m_i}))$ that is weighted by the failure probability $p_{m_i,t}$. Note that this failure probability depends on the week of execution, i.e., it might be higher if the intervention is shifted into the next week.

Moreover, each intervention needs to fit either in the available train free periods or in the possession times resulting from the tactical plan. This is ensured by the condition

$$\begin{aligned} \forall i \in I_t^D \,\big(\exists j \in \{1, \dots, k_f^D\} \left((f_j^2 - f_j^1) \ge \mathbb{E}(\varrho_{m_i})\right) \vee \\ \exists j \in \{1, \dots, k_v^D\} \left((v_j^2 - v_j^1) \ge \mathbb{E}(\varrho_{m_i})\right)\big)\,, \end{aligned} \tag{22}$$

where we demand that for all interventions it exists for the corresponding signaling section a time window (either train free period or possession window) with a longer duration than the expected duration of the intervention. Otherwise, the intervention can not be executed and we would have to split the intervention into shorter ones.

2.3 Alignment between output from WP4 and input for WP6

We describe the handling of output from the Alert Generation (AG) module developed in WP6 to be aligned with the required input for the Decision Support (DS) module in WP4, with particular focus on the mathematical model for the road use case, stated above in (1)-(9).

In the following a fixed asset a at a certain time (scenario) t is considered. To simplify notation, indices related to asset and time are omitted in all definitions using the following conventions:

- Feature values $x_1(t), \ldots, x_p(t)$ are known (from measurement) until time t_0, i.e. for times $t \leq t_0$.
- Feature values $x_i(t_0)$ for a certain future time $t_1 > t_0$ are unknown but can be predicted, thus are considered to be random variables with known PDF $F_i \equiv F_{i,t_1}$ where

$$F_i(x) = P(x_i(t_1) \leq x | x_i(t_0))$$

- A predicted value at time t_1 is simply denoted by $\hat{x}_i = x_i(t_1)$.
- Quality index $q(t)$ (for asset a at time t) is calculated using a certain function

$$q(t) \equiv q(x_1(t), \ldots, x_p(t))$$

There are two possibilities for generating alerts described in Deliverable D4.2, both requiring different handling of its output.

2.3.1 Variant 1: AG via fixed rules using feature levels

In this variant, alerts are assumed to be deterministically derived from known feature values, according to the rules defined by combinations of features levels as follows.

- Feature levels define a disjoint partition of $\mathbb{R}$ into three intervals

$$L_i = (-\infty, l_i), M_i = [l_i, r_i], H_i = (r_i, +\infty)$$

  for each feature i.
- Probability for $\hat{x}_i \in M_i$ (resp. L_i or H_i) at time t_1 follows from F_i, e.g.

$$p_i^M := P(\hat{x}_i \in M_i) = F_i(r_i) - F_i(l_i)$$

- An alert A_j is defined as a combination of several features being in certain levels at considered time t, e.g.

$$A_j : \hat{x}_1 \in M_1 \wedge \hat{x}_2(t) \in M_2 \wedge \hat{x}_3(t) \in H_3$$

- Alert A_j can be seen as random event occuring with probability p_j, e.g.

$$p_j := P(A_j) = p_1^M \cdot p_2^M \cdot p_3^H$$

- With each alert A_j a certain intervention is associated which is used to fix the respective problem of the asset.

Terminology used in modelling of DS is slightly different: Here, a degradation level correlates with an alert, the probability of an asset being in a certain degradation level is required. Thus, the input for DS can be achieved directly as the probabilities p_j.

2.3.2 Variant 2: AG via learning from historical intervention records

In this more general view on alerts their occurrences are learned from historical intervention records as follows:

- Given (predicted) feature values $\hat{x}_i$ at time t_1, AG applies Machine Learning methods to derive possible interventions and their probabilities, i.e. a vector of probabilities

$$\pi = (\pi_1, \dots, \pi_m)$$

  with π_j being the probability that alert A_j of possible alerts $A_1, \dots, A_m$ is generated (i.e. the associated intervention has to be applied). Note that π_j is a conditional probability, i.e.

$$\pi_j = P(A_j | \hat{x}_1, \dots, \hat{x}_p).$$

  With other words π_j describes the probability that alert A_j is generated under the condition that the feature values are predicted by $\hat{x}_1, \dots, \hat{x}_p$.

- From the methodology used in AG, the resulting vector does not has to be a probability vector (i.e. summing up to 1), but it is assumed that the used π is normalised.

The first variant can be seen as a special case of this more general, in which AG always produces the single deterministic alert according to the fixed rule. (π is then a unit vector.).

To derive the required input for DS it es necessary to calculate the unconditioned probabilities of alerts. This can be done via sampling of future feature values using their PDFs F_i:

- Given N sample scenarios $(\hat{x}_1^{(k)}, \dots, \hat{x}_p^{(k)})$ for $k = 1, \dots, N$.
- AG module produces $\pi^{(k)} = (\pi_1^{(k)}, \dots, \pi_m^{(k)})$ for each sample $k = 1, \dots, N$.
- Set $p_j = P(A_j) = \frac{1}{N} \sum_{k=1}^{N} \pi_j^{(k)}$.

3 Optimisation Algorithms

The planning problems presented in the Sections 2.1.2 and 2.2.2.2 are solved by the Monte-Carlo Rollout method. The method generates a set different solutions and selects the best alternative based on an evaluation value, which results from simulated future scenarios. This Chapter is structured as follows: We start with the analysis of the input data in Section 3.1. Further we investigate in Section 3.2 the Monte-Carlo Rollout method, which is applied to the tactical planning problem in Section 3.2.4.

3.1 Input Data

3.1.1 Road Use case

The following flowchart illustrates the exchange of information in order to provide the input data for the decision support in the road use case. Based on the current network state WP3 predicts future networks states which forms the basis for WP4, where the most probable interventions and the corresponding probabilities for the predicted network states are computed. This most probable interventions as well as some additional user information about the weighting factors of the KPI's form the required input for the decision support tool.

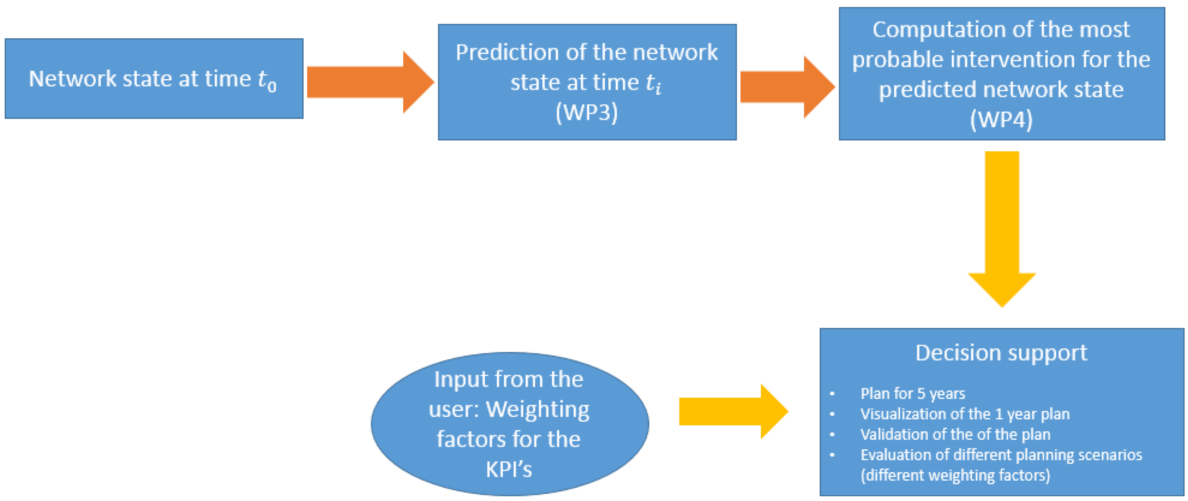

Figure 8: Flowchart

More precisely, we consider a network at its current state at the time t_0, i.e., we take into account for each asset the feature level condition. In the road use case we consider the segments of a section as an asset the corresponding features are CT, IRI and RUT (in the following they are denoted by

y_1, y_2, y_3). To specify the structure of the input data we illustrate its definition using the small example network shown in Figure 9.

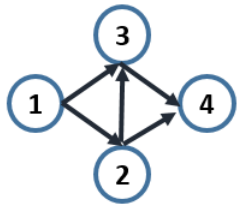

Figure 9: Example network

Following Example 9 the definition of the network topology can be done via the Tables 2-5. The definition of the network as well as the information about the origin destination pairs provided in Table 6 are the input for the analysis of the influence of the traffic described in Section 2.1.3.

Knots: ID	x-coordinate	y-coordinate
1	0	2
2	2	0
3	2	4
4	4	2

Table 2: Definition knots

Edges: ID 1→ID 2		section ID	capacity	length	average speed	bidirectional
ID 1	ID 2					
1	2	1	12	2	45	1
1	3	2	25	2	30	1
2	3	3	15	1	60	0
2	4	4	15	2	45	1
3	4	5	25	2	45	1

Table 3: Definition edges (sections)

Table 8 provides a list of interventions that have to be executed in the planning year. Each intervention is specified by the feature values after the intervention (they describe the initial value $y_i^{(0)}$ of the different features), capacity reduction in % of the road caused by the intervention (needed in the analysis tool regarding the influence on the traffic). Moreover, further information of the intervention

Assets: Asset ID	section	region	start	end	IRI_t	CT_t	RUT_t	quality threshold
12	4	9	14	14.5				20
13	4	9	14.5	15				45
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 4: Current status of the asset (segment)

Supervisory staff: region	staff capacity
9	4
10	4
⋮	⋮

Table 5: Capacity of the supervisory staff per region

OD-pairs: ID 1→ID 2 ID 1	ID 2	demand
1	4	25

Table 6: OD pairs: Demand for the origin-destination pairs

monthly: Intervention type	Month	cost per km	duration
T1	1	35.000	2.5
T1	2	30.000	2
T1	3	28.000	2
T1	4	30.000	2
⋮	⋮	⋮	⋮
T2 ⋮	1 ⋮	40.000 ⋮	4 ⋮

Table 7: Definition of the interventions (depending on the moth of execution)

definition: Intervention type	feature value after intervention			capacity red. (in %)
	CT^0	IRI^0	RUT^0	
T1	1.2	0.2	0.6	50
T2	0.6	0.3	0.7	75
⋮	⋮	⋮	⋮	⋮

Table 8: List of interventions (planning year)

like costs per kilometre and duration of the intervention are provided in Table 7. Note that both properties depend on the the month of execution.

Preprocessing

The generation of the input data can be divided into three steps. We start with an initialization step, where the corresponding function is called "FeatureInit" in the following.

To reduce the computation complexity, we cluster in a first step the current states of the different features (CT, IRI and RUT) of all assets. Further, we sequentially compute for the next 60 months for each cluster c_i with $i = 1, \ldots, n$ different scenarios s_l with $l = 1, \ldots, k$. In other words we ask for a result of the form: "At time t_j" the cluster c_i will have the feature value y_i". Additionally we have to compute again k different scenarios for the next 60 months for the initial states of the 3 features CT^0, IRI^0 and RUT^0. This prediction step should be provided by WP3, i.e., WP3 needs to complete Table 9.

In the second step we have to generate alerts, which is realised by the function "AlertGeneration".

feature value CI:				
cluster	scenario	t_1	$\dots$	t_{60}
c_1	s_1			
	s_2			
	$\vdots$			
	s_k			
c_2	s_1			
	s_2			
	$\vdots$			
	s_k			
$\vdots$	$\vdots$			
c_n	s_1			
	s_2			
	$\vdots$			
	s_k			
CI^0_{T1}	s_1			
	s_2			
	$\vdots$			
	s_k			
CI^0_{T2}	s_1			
	s_2			
	$\vdots$			
	s_k			
CI^0_{T3}	s_1			
	s_2			
	$\vdots$			
	s_k			
CI^0_{T31}	s_1			
	s_2			
	$\vdots$			
	s_k			
CI^0_{T4}	s_1			
	s_2			
	$\vdots$			
	s_k			

feature value IRI:				
cluster	scenario	t_1	$\dots$	t_{60}
c_1	s_1			
	s_2			
	$\vdots$			
	s_k			
c_2	s_1			
	s_2			
	$\vdots$			
	s_k			
$\vdots$	$\vdots$			
c_n	s_1			
	s_2			
	$\vdots$			
	s_k			
IRI^0_{T1}	s_1			
	s_2			
	$\vdots$			
	s_k			
IRI^0_{T2}	s_1			
	s_2			
	$\vdots$			
	s_k			
IRI^0_{T3}	s_1			
	s_2			
	$\vdots$			
	s_k			
IRI^0_{T31}	s_1			
	s_2			
	$\vdots$			
	s_k			
IRI^0_{T4}	s_1			
	s_2			
	$\vdots$			
	s_k			

feature value RUT:				
cluster	scenario	t_1	$\dots$	t_{60}
c_1	s_1			
	s_2			
	$\vdots$			
	s_k			
c_2	s_1			
	s_2			
	$\vdots$			
	s_k			
$\vdots$	$\vdots$			
c_n	s_1			
	s_2			
	$\vdots$			
	s_k			
RUT^0_{T1}	s_1			
	s_2			
	$\vdots$			
	s_k			
RUT^0_{T2}	s_1			
	s_2			
	$\vdots$			
	s_k			
RUT^0_{T3}	s_1			
	s_2			
	$\vdots$			
	s_k			
RUT^0_{T31}	s_1			
	s_2			
	$\vdots$			
	s_k			
RUT^0_{T4}	s_1			
	s_2			
	$\vdots$			
	s_k			

Table 9: Current and initial feature values

Current status: asset ID	scenario ID	time	T_0	T_1	T_2	T_3	T_4
1	s_1	t_1					
		$\vdots$					
		t_{60}					
	s_2	t_1					
		$\vdots$					
		t_{60}					
	$\vdots$	$\vdots$					
	s_k	t_1					
		$\vdots$					
		t_{60}					
2	s_1	t_1					
$\vdots$	$\vdots$	$\vdots$					

Table 10: Current status of the asset

On the basis of the different scenarios initialized by WP3 in the first step, WP4 computes for each month $t_1, \ldots, t_{60}$ for the k different scenarios the required intervention for the asset x. Note that WP4 does not only provide one intervention solving the alert, but the most probable interventions and its corresponding probabilities. In WP4 the alerts are generated via a learning procedure that is based on historical intervention data. The result for each asset is presented in the Tables 10-15. In the first table the probabilities of the interventions corresponding to the asset in its current state are shown. The other Tables 11-15 illustrate the probability of the interventions corresponding to the initial state of the asset. In particular, the Tables 11-15 are of interest because they describe the status of an asset after the corresponding intervention.

Finally we have to compute the influence matrix in order tu evaluate the effect of the intervention on the traffic. This is done by the function ”InfluenceCalc”.

More precisely if we have to realize two interventions at the same point of time, we are interested in combination possibilities of the interventions that still guarantee a sufficient network quality. Input for this preprocessing step are the network topology (stated in the Tables 2 and 3) and the demand of the network (given by the OD pairs in Table 6). The results in a influence matrix that illustrates the degree of capacity utilization if the considered interventions are executed.

Computation of the tactical plan

Finally, after the preprocessing steps mentioned in the previous section all information are available to start the computation of the tactical plan (5 years). Beside the most probable interventions and the corresponding probabilities we additional need some user specific information stated in the fol-

Initial status T1: asset ID	scenario ID	time	T_0	T_1	T_2	T_3	T_4
1	s_1	t_1					
		$\vdots$					
		t_{60}					
	s_2	t_1					
		$\vdots$					
		t_{60}					
	$\vdots$	$\vdots$					
	s_k	t_1					
		$\vdots$					
		t_{60}					
2	s_1	t_1					
$\vdots$	$\vdots$	$\vdots$					

Table 11: Status of the asset after the intervention T1

Initial status T2: asset ID	scenario ID	time	T_0	T_1	T_2	T_3	T_4
1	s_1	t_1					
		$\vdots$					
		t_{60}					
	s_2	t_1					
		$\vdots$					
		t_{60}					
	$\vdots$	$\vdots$					
	s_k	t_1					
		$\vdots$					
		t_{60}					
2	s_1	t_1					
$\vdots$	$\vdots$	$\vdots$					

Table 12: Status of the asset after the intervention T2

Initial status T3: asset ID	scenario ID	time	T_0	T_1	T_2	T_3	T_4
1	s_1	t_1					
		$\vdots$					
		t_{60}					
	s_2	t_1					
		$\vdots$					
		t_{60}					
	$\vdots$	$\vdots$					
	s_k	t_1					
		$\vdots$					
		t_{60}					
2	s_1	t_1					
$\vdots$	$\vdots$	$\vdots$					

Table 13: Status of the asset after the intervention T3

Initial status T31: asset ID	scenario ID	time	T_0	T_1	T_2	T_3	T_4
1	s_1	t_1					
		$\vdots$					
		t_{60}					
	s_2	t_1					
		$\vdots$					
		t_{60}					
	$\vdots$	$\vdots$					
	s_k	t_1					
		$\vdots$					
		t_{60}					
2	s_1	t_1					
$\vdots$	$\vdots$	$\vdots$					

Table 14: Status of the asset after the intervention T3.1

Initial status T4: asset ID	scenario ID	time	T_0	T_1	T_2	T_3	T_4
1	s_1	t_1					
		$\vdots$					
		t_{60}					
	s_2	t_1					
		$\vdots$					
		t_{60}					
	$\vdots$	$\vdots$					
	s_k	t_1					
		$\vdots$					
		t_{60}					
2	s_1	t_1					
$\vdots$	$\vdots$	$\vdots$					

Table 15: Status of the asset after the intervention T4

Influence matrix: Section ID1	Intervention type	Section ID2	Intervention type	degree of utilization
$1 \to 2$	T1	$1 \to 3$	T2	95%
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Table 16: Influence matrix

Tactical plan (5 years): asset	time	interven-tion
x_1	month 12	T3
x_1	month 30	T2
$\vdots$	$\vdots$	$\vdots$

Table 17: Tactical plan

lowing:

- The user provides a set of weighting factors, i.e., how he rates the importance of the three KPI's (costs, network availability, quality). The weighting factors are chosen by slider controls in the range $[0, 1]$.
- User provides parameter to control the robustness which is a value in $[0, 1]$.
- User provides budget restrictions (annual and for the next 5 years).

Based on the above information we compute the tactical plan for the next 5 years. The structure of the resulting plan is presented in Table 17.

Flowchart

In order to show the interaction of the different WP's we provide in Figure 10 an overview of the flow of information in this use case.

Asset: asset ID	signaling section
25	23
54	27
113	04
⋮	⋮

Table 18: Assets rail network

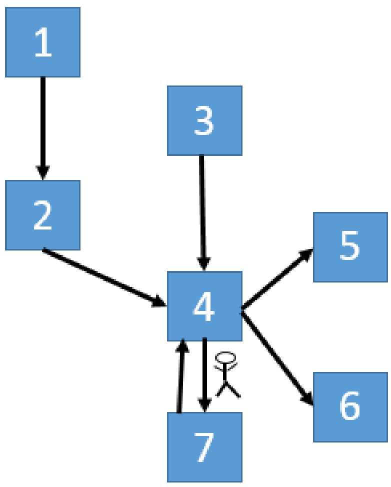

Figure 10: Flowchart road use case

3.1.2 Rail use case

In the rail use case the line is divided in signalling sections and each asset belongs to a certain signalling section. This leads to the formal description of an asset presented in Table 18.

The annual tactical plan and the corresponding booking of the possession times can be considered as given. A representation of the data structure of this input is given in the Tables 19 and 20. Note that during the possession time the whole line is blocked. Consequently, the signalling sections that are not occupied by the ”large” maintenance activities that come from the tactical plan, can be used for ”small” maintenance activities that have to be arranged in the dynamical plan.

Additional to the possession time we can use on the short time horizon of the dynamic plan the so called train free periods. This periods are determined by the current train schedule, i.e., they are restricted to signalling sections and in comparison to the possession time windows is the duration of

Possession time: Line ID	start time	end time
1	22.04.2017 23:00	23.04.2017 6:00
4	25.04.2017 21:00	26.04.2017 5:00
4	05.04.2017 23:00	06.04.2017 6:00
⋮	⋮	⋮

Table 19: Possession time

Tactical plan: Asset ID	Signaling section	Intervention type	start time	end time
66	7	tamping	22.04.2017 24:00	23.04.2017 06:00
56	10	repair welding	25.04.2017 24:00	26.04.2017 02:00
95	2	line grinding	15.04.2017 22:00	16.04.2017 04:00
44	15	crossing replacement	05.04.2017 23:00	06.04.2017 03:00

Table 20: Tactical plan

such a train free period shorter. The data structure of the train free periods is presented in Table 21.

Further, the list of possible interventions are stated in Table 22. Here an intervention is defined by its corresponding asset ID, failure mode ID and action ID.

The additional information corresponding to each intervention like costs, repair times are provided via stochastic data. In particular, the costs are defined by a confidence interval, i.e., as shown in Table 23 for each action ID the costs and the corresponding confidence interval and level is known.

The repair times are provided via a distribution function, thus for the corresponding failure mode ID we know the distribution family which is specified by the corresponding scale and location parameter, see Table 24.

Train free periods: Signaling section ID	start time	end time
34	26.04.2017 23:00	27.04.2017 1:00
24	27.04.2017 24:00	28.04.2017 2:00
13	28.04.2017 23:00	09.04.2017 3:00
⋮	⋮	⋮

Table 21: Train free periods

Interventions: Asset ID	Failure mode ID	Action ID
34	123	60
24	129	12
13	139	45
⋮	⋮	⋮

Table 22: List of interventions

Costs: Action ID	costs	lower bound	upper bound	confidence level
34	6000	5000	7000	95%
4	12000	10000	14000	98%
10	6000	5000	7000	95%
⋮	⋮	⋮	⋮	⋮

Table 23: Costs of intervention

MTTR: Failure mode ID	distribution family	location parameter	scale parameter
34	log	5	2
4	log	100	3
10	log	-30	0.2
⋮	⋮	⋮	⋮

Table 24: Mean time to repair (MTTR)

Failure probability: Failure mode ID	$F(t+9w)$	$F(t+10w)$
34	6%	12%
4	3%	8%
10	5%	6%
⋮	⋮	⋮

Table 25: Failure probability

Down time: Failure mode ID	distribution family	location parameter	scale parameter
34	log	5	0.5
4	log	-10	10
10	log	3	2
⋮	⋮	⋮	⋮

Table 26: Downtime

Also the failure probability and the down time of the asset are provided via stochastic data. As stated in Table 25 we know for each failure mode the corresponding failure probability of week 9 and week 10. The downtime caused by failures is also defined by a distribution function, i.e., as stated in Table 26 for each failure mode the distribution function with the corresponding location and scale parameters are known.

Computation of the list of interventions for the planning week

Additional to the above informations we need the following user specific data:

- User provides a set of weighting factors, i.e., he rates the importance of the KPI's (costs, reliability). Those factors are chosen by slider controls in the range $[0, 1]$.
- User provides restrictions on the one week budget and the required reliability.

Thus, we can now compute the list of the actions planed for the next week and the list of all interventions that needs to be shifted into the next week.

Flowchart

The rail use case is mostly based on data resulting from the RAMS and LCC analysis and user specific input data. This is also represented in the flowchart in Figure 11.

Actions week 1: Action ID	Shifted interventions : Action ID
1	1
14	14
7	7
⋮	⋮

Table 27: Result of the short term planning

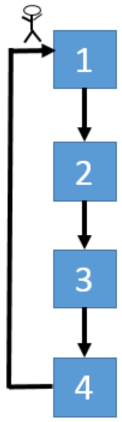

Figure 11: Flowchart rail use case

3.2 A Simulation-based Solution Method

The developed solution procedure – the so-called Monte-Carlo Rollout method – is based on simulated scenarios and combines ideas from rollout algorithms and Monte-Carlo tree search 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 the 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 of an alternative, but also the quality and availability of the alternatives is evaluated and considered when selecting the best solution. In the following the Rollout algorithm and the Monte-Carlo tree search will be briefly described. Afterwards the Monte-Carlo Rollout method is presented in detail and its application to the tactical planning problem is shown.

3.2.1 Rollout Algorithms

Rollout algorithms [7, 8] can be used for optimization problems that have a sequential structure, i.e. that can be solved by making a sequence of consecutive decision steps. In every step we have a limited number of alternatives and we want to choose the alternative which leads to the best overall solution. By means of the Rollout method, each alternative decision is evaluated in order to choose in each decision step the best alternative. The Rollout algorithm iteratively explores all different alternatives in the current decision step. It uses a so-called base heuristic for making decisions in the steps following the current decision. The base heuristic usually is a fast, rather simple but solid heuristic for the problem at hand, that solves the problem in a sequential manner. With the help of this base heuristic the Rollout algorithm gets an evaluation of the alternative in the current decision step at a leaf of the tree, namely at that leaf that would be reached if the base heuristic would be applied (after choosing the alternative considered). After evaluating all alternatives in the current step, the one that leads to the best results under the base heuristic is chosen.

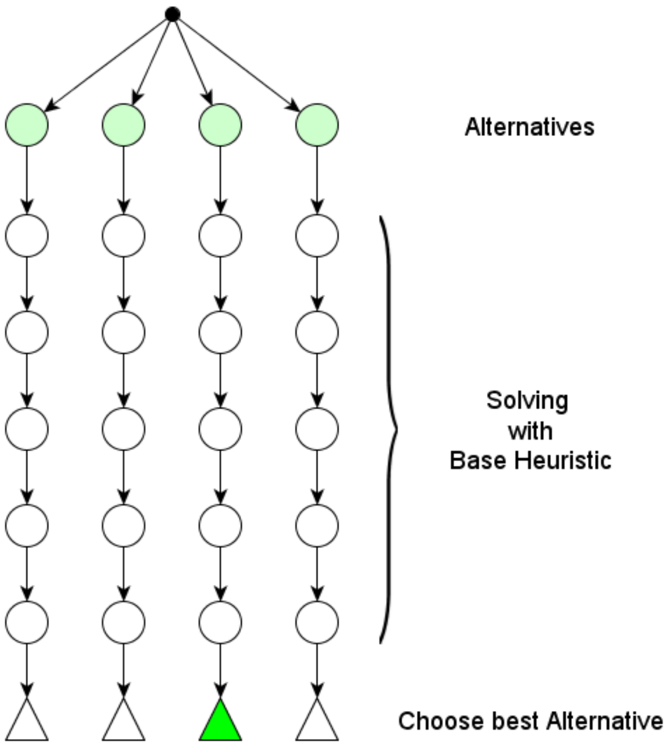

Figure 12: Schematic representation of the Rollout approach

In Figure 12 the Rollout algorithm is illustrated by a schematic representation. The initial point is the set of past decisions which leads to the current stage of the problem. Now we have a limited set of possible alternatives. For each alternative we estimate the solution quality by solving the problem with the base heuristic and determine the objective value of the generated solution.

3.2.2 Monte-Carlo tree search

The Monte-Carlo Tree Search (MCTS) [9, 10, 11] first was developed for computers to play the board game Go, but in the meantime it is the state-of-the-art technique for a set of single- or multi-person games. The main idea is as follows: At first we only have the root of the game tree. This is the initial point of the first decision, i.e. the move of the player to turn. There are different alternatives for the next move and we want to find the best alternative without exploring the whole decision tree. By the MCTS we evaluate the nodes in the tree based on random games. Monte-Carlo tree search is used for problems where no good heuristic was found to evaluate a decision.

Instead of using a noisy and possible misleading heuristic evaluation, the alternative decisions are evaluated by means of random games. Often there are game-specific information about the quality of moves which can be used to weight the possible moves.

3.2.3 The Monte-Carlo Rollout method

The Monte-Carlo-Rollout [12, 13] approach combines the ideas of the Rollout algorithm and the Monte-Carlo Tree Search. The approach can be used to handle sequential optimisation From the rollout method comes the idea to evaluate an alternative solution by solving the problem further with 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. So the optimisation problem with uncertainties is modelled as a two-player game. 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 13.

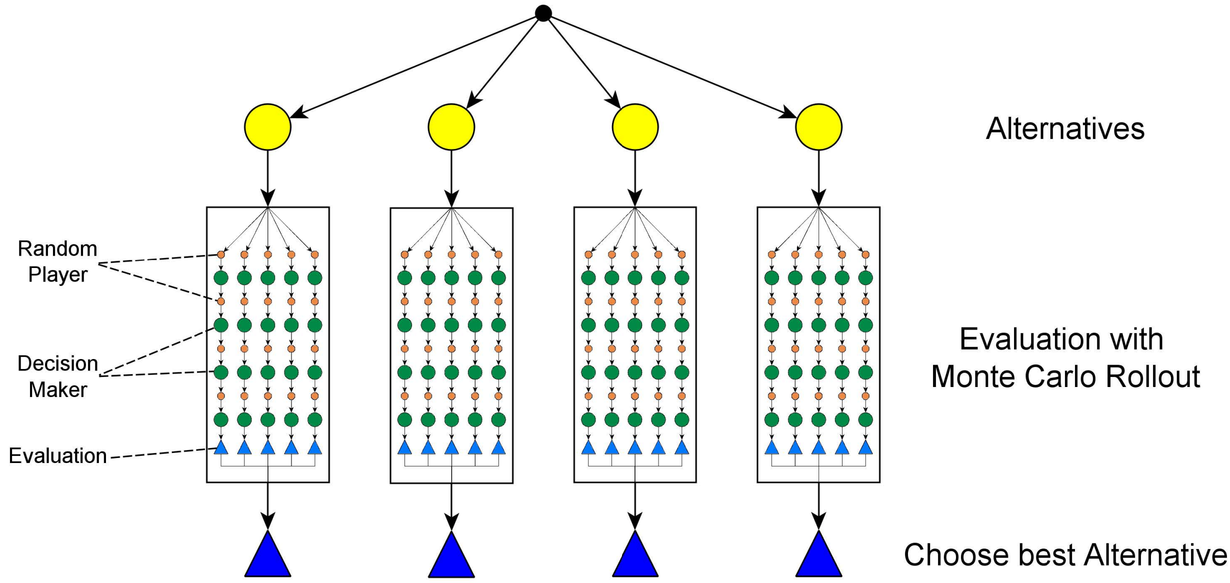

Figure 13: Schematic representation of Monte-Carlo Rollout method

The Monte-Carlo Rollout method works as follows: Initially a set of different alternative solutions is generated (the yellow dots in Figure 13). Each of these alternatives is proven and evaluated by a number of Monte-Carlo Rollouts (subsumed in the boxes, each string of orange and green dots is one Monte-Carlo Rollout). In each Monte-Carlo Rollout another future scenario is played in terms of a two-player game. Thereby a stochastic model is used to simulate random events (moves of the random player, orange dots), and the changed situation is solved using the base heuristic H (moves of the decision maker, green dots). The two players move consecutively until the end of the game or a predefined number of steps (the depth) is reached. The outcome of each scenario is evaluated (represented in the scheme through the small blue triangles), and the solution quality of the alternative is determined, e.g. by averaging scenario evaluations (big blue triangles). After all the best alternative, thus the alternative with the best evaluation value, is chosen, being a high-quality solution additionally equipped with high robustness.

3.2.4 Application of the Monte-Carlo Rollout Method

The generation of the interventions plan can be divided into two steps, as described in the following by means of the exemplary use case for the tactical planning in the road network: 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.

3.2.4.1 First Planning Step

The starting point of this considerations form n_s different scenarios of possible future developments of the asset conditions. In the first step we have to generate the intervention events for all possible intervention levels, sections and planning years. In more detail 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 in the time step t, where $t \in \{1, \ldots, 5\}$ describes the execution year. This procedure results into 5 intervention events per section for each time step $t \in \{1, \ldots, 5\}$, i.e., we obtain a list of 5×5 intervention events per section.

In the following we want to generate a plan, thus we have to specify for each section which intervention level should be applied and in which year should we execute the resulting intervention event. This problem is modelled via a bin packing problem, where each bin symbolizes one year of the planning horizon. The packing of the bins is realized using a First-Fit heuristic, presented in the following section.

3.2.4.1.1 The First-Fit Heuristic

The First-Fit heuristic starts with the prioritisation of the event intervention, thus we prioritize a list $\mathcal{E}$ that includes all intervention events of the different sections, intervention levels and time steps, i.e., we prioritize a list of $5 \times 5 \times n_b$ 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

$$\Delta c_e(t) := \sum_{i=1}^{n_s} \left(\sum_{m=1}^{12} \frac{\mathbb{E}(c_e(12t+m,i))}{12} - \sum_{m=1}^{12} \frac{\mathbb{E}(c_e(12(t-1)+m,i))}{12} \right) / n_s \qquad \forall t \in \{1, \ldots, 5\}.$$

  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

$$\bar{q}_e(t) = \sum_{i=1}^{n_s} \sum_{m=1}^{12} \left(\sum_{a \in e} q_a(12t+m,i) \right) / 12 n_s \qquad \forall t \in \{1, \ldots, 5\}.$$

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

$$g_e(t) := \lambda_1 \Delta c_e(t) + \lambda_2 \bar{q}_e(t), \tag{23}$$

where λ_1 and λ_2 are user dependent parameter, i.e., this parameter represent the user preferences regarding costs and quality. In Algorithm 4 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 4 First-Fit Heuristic

Generate a list of all possible intervention events $\mathcal{E}$
Compute the priority measure g_e for all $e \in \mathcal{E}$
while $\mathcal{E}$ nonempty **do**
  Choose event $e^*(t^*, b^*, \ell^*)$ with $g_{e^*} = \max_{e \in \mathcal{E}} g_e$
  if $\sum_{e \in \mathcal{E}: x(e,t^*)=1} c_e + c_{e^*} < C_{t^*}$ & $\sum_{e \in \mathcal{E}: x(e,t^*)=1 \wedge r_e \in r} 1 \leq 12 n_r \quad \forall r \in R$ **then**
    $x(e^*, t^*) = 1$
    Remove all intervention events corresponding to section b^* from list $\mathcal{E}$
  else
    Remove intervention event $e^*(t^*, b^*, \ell^*)$ from list $\mathcal{E}$
  end if
end while

We start in the first step with the generation of a list $\mathcal{E}$ 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 (23), for each event intervention of the list $\mathcal{E}$. 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 the event intervention we remove all other event interventions from the list $\mathcal{E}$ that correspond to section b^*. If the event intervention does not fit into the corresponding planning year, i.e., the event intervention violates the constraints, we just remove this specific event from the list and continue with the algorithm. Finally, if list $\mathcal{E}$ is empty we managed to construct one possible plan x.

3.2.4.1.2 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 high-quality solution that is equipped with high robustness. The pseudo code of the Monte-Carlo Rollout method is provided in Algorithm 5. For the corresponding analysis we need 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 the costs, quality and availability of a certain plan.

Algorithm 5 Monte-Carlo Rollout

1: Generate a list of all possible intervention events $\mathcal{E}$
2: Compute the priority measure g_e
3: **while** $\mathcal{E}$ nonempty **do**
4: Choose event $e^*(t^*, b^*, \ell^*)$ with max g_e^*
5: **for all** Events $\{e_0, e_1, \ldots, e_k\}$ corresponding to the section b^* **do**
6: **if** $\sum\limits_{e \in \mathcal{E}: x(e,t^*)=1} c_e + c_{e_i} < C_{t_i}$ & $\sum\limits_{e \in \mathcal{E}: x(e,t^*)=1 \wedge r_e \in r} 1 \leq 12 n_r \quad \forall r \in R$ **then**
7: $x_i(e_i, t_i) = 1$
8: $\mathcal{E}' := \mathcal{E} \setminus \{e_0, e_1, \ldots, e_k\}$
9: Compute x_i by applying the `First-Fit Heuristic` (Algorithm 4) to $\mathcal{E}'$
10: **for all** Scenarios $\sigma_1, \ldots, \sigma_{n_s}$ **do**
11: Compute $f_j(x_i) := \alpha_1 c(x_i) + \alpha_2 q(x_i) + \alpha_3 v(x_i)$
12: **end for**
13: Compute $\bar{f}(x_i) = \left(\sum\limits_{j=1}^{n_s} f_j(x_i) \right) / n_s$
14: **end if**
15: **end for**
16: Choose event e_{max} with $\bar{f}(x_{\text{max}}) = \max\limits_{i \in \{0,1,\ldots,k\}} \bar{f}(x_i)$
17: Remove intervention events $\{e_0, e_1, \ldots, e_k\}$ corresponding to section b^* from list $\mathcal{E}$
18: **end while**

The starting point is the generation of a list collecting all possible intervention events, i.e., the list $\mathcal{E}$ contains all intervention intervention events for all segments, all interventions levels and all time steps of the planning horizon. Further, we compute for each intervention event, based on (23), the priority measure g_e and determine the section b^* that corresponds to the intervention event with the highest priority. Now we are analysing the situation for all possible event interventions $\{e_0, e_1, \ldots, e_k\}$ that could be executed on the section b^*. Therefore, we check for each intervention event whether the constraints regarding the budget and the capacity in Step 6 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 $\mathcal{E} \setminus \{e_0, e_1, \ldots, e_k\}$. 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 choose form $\{e_0, e_1, \ldots, e_k\}$ the intervention event e_{max} with the highest evaluation value $\bar{f}(x_{\text{max}})$ and remove all interventions events from the list $\mathcal{E}$ that belong to the section b^*. We continue with this algorithm until the list $\mathcal{E}$ 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.

3.2.4.2 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 $\Delta(\mathbb{E}\left(T_{down}\right)P_{failure})$ for month 1 and 12 of the planning year, i.e., we consider a priority measure of the form

$$h_e := \alpha_1 \Delta c_e + \alpha_2 \left(\Delta q_e + \Delta(\mathbb{E}\left(T_{down}\right)P_{failure})\right), \tag{24}$$

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 probability of failure and the expected downtime due to the failure.

Based on the measure (24) 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 6, where x_i^m describes the monthly plan of the planning year i.

Algorithm 6 Monthly allocation

1: **for all** Planning years $i \in \{1, 2, \ldots, 5\}$ **do**
2: Consider the list of intervention events $\mathcal{E}_i$ 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 $\mathcal{E}_i \setminus e^*$ such that
$v(G, f)$ does not decrease more than n% and
$$\sum_{e \in \mathcal{E}_i : x_i^m(e,j)=1 \wedge r_e \in r} 1 \leq n_r \quad \forall r \in R$$
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 $\mathcal{E}_i$
12: **end for**
13: **end for**

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4 Conclusion and Outlook

Conclusion

In this deliverable we considered the mathematical modelling and algorithm design for the operational and tactical maintenance planning. Therefore, we investigated two use cases. In the first use case we analysed 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)

The second use case is based on data from TrV. We investigated mainly the operational planning level and concentrate on:

- Using stochastic information
- Combine tactical and dynamical planning for a better usage of possession time
- Integration of the possibility to get a refund in case of unused possession time

In general we focused for both use cases 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 cases.

Future work and Outlook

Implementation of decision support tools naturally is an iterative process, including several loops of refinements after validation of results in testing scenarios. The state of the tools presented in this first version of the document represents a version ready for practical tests in the demonstrator pilots. Some details both of the mathematical modelling as well as of the algorithmic implementation will be further developed and adapted according to requirements and findings from evaluations of test

runnings. All parts of the used methodology are implemented in a way that an easy adaptbility is possible.

Also, note that the work in WP6 will continue across the whole lifetime of INFRALERT. Hence, for the sake of actuality, this Deliverable D6.2 will become a living document updated regularly whenever needed.

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