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Abstract

Within the ACEM-Rail project of the European Seventh Framework Programme new measurement and inspection techniques for monitoring the track condition are developed. By means of these new techniques the prediction of future track condition will be highly improved. To our knowledge mid-term maintenance planning is done for projects and preventive tasks, but predictions of the track condition are not incorporated into the planning process up to now. To efficiently utilise this new kind of information one task within the ACEM-Rail project is the development of methods for planning predictive maintenance tasks along with preventive and corrective ones in a mid-term planning horizon. The scope of the mid-term or tactical maintenance planning is the selection and combination of tasks and the allocation of tasks to time intervals where they will be executed. Thereby a coarse maintenance plan is determined that defines which tasks are combined together to form greater tasks as well as the time intervals for executing the selected tasks. This tactical plan serves as the base for booking future track possessions and for scheduling the maintenance tasks in detail.

In this paper an algorithmic approach is presented which is able to react on dynamic and uncertain changes due to any track prediction updating. To this end optimisation algorithms are implemented within a rolling planning process, so it is possible to respond to updated information on track condition by adapting the tactical plan. A novel optimisation method is developed to generate cost-effective and robust solutions by looking ahead into the future and evaluating different solutions in several scenarios.

Keywords: Railway Maintenance, Tactical Planning, Optimisation under Uncertainty

1 Introduction

Tactical planning is an important step in the process of planning railway maintenance activities. It involves the selection and combination of maintenance tasks and their allocation to time intervals ("slots") where they will be executed.

As a side-effect the tactical plan impacts track possession booking. Tactical planning is done in a mid-term horizon, typically for nine to twelve months. Nobody knows the real track condition evolving within this period of time, only predictions can be made. Of course, these predictions are always afflicted with uncertainties. So uncertain predictions are the input to the tactical planning, which lead to probabilities for different track conditions (or level of severities) over time.

In this paper we present a novel optimisation model for tactical planning along with a solution method dealing with uncertain track conditions. The main idea of our approach is to create maintenance plans by periodically adaption and extension of the previous plan. Thereby booked track possession leads to a fixation of maintenance activities to time slots. Non-fixed activities can be shifted to other slots, if it is feasible and beneficial. In this way the planning process is able to react on new situations, resulting from new track measurement data and predictions, and rectify uncertainties. Moreover the algorithm takes a look into the future by simulating different future scenarios. This leads to a robust solution, mainly to a robust track possession booking.

Only a limited number of works can be found dealing with tactical maintenance planning. In [1] the Preventive Maintenance Scheduling Problem (PMSP) is defined and solved using simple heuristics. The PMSP is focused on preventive and periodically executed maintenance tasks plus larger projects, predictive maintenance activities are not considered. In [2] a method of constructing a four-week, cyclic, preventive maintenance schedule is described. Aim of the schedule is to handle the dictate to close the track for all trains when maintenance tasks are executed.

2 Modelling of Tactical Planning Process and Uncertainties

In this section we describe our approach to the tactical railway maintenance planning under uncertain track conditions. In 2.1 the concept of maintenance warnings will be introduced, while 2.2 describes the tactical planning process.

2.1 Warnings

In our model we refer to predictive or corrective maintenance activities that are generated based on the actual or predicted track condition as “warnings”. The challenge in tactical planning is to combine or divide warnings and allocate the corresponding tasks to time slots, thereby fulfil given constraints. The resulting allocation aims to be cost effective and robust to uncertain future conditions, as the plan is the base for booking track possession and executing maintenance tasks in short term.

Warnings are created in a preliminary step by the Maintenance Management System based on track measurement data and predicted conditions. We distinguish three kinds: basic, combined, and divided warnings. For each problem on the track all possible kinds of warnings are generated and in the planning process exactly one of them is selected. Normally basic warnings can be executed during one night by one team. Sometimes there is a possibility to combine the basic warnings of different problems on consecutive track sections to get one great combined warning. For combined warnings the track has to be closed longer than one night because of the long working duration. Hence additional costs for booking the track are incurred. On the other hand, the maintenance team has to travel only once to the track section which leads to lower travel costs. Another possibility is to divide a basic warning into smaller parts, resulting in so-called divided warnings that can be resolved manually. Mostly manual resolving is very time intensive but the machineries used are smaller and cheaper. Sometimes thus it is cost effective to resolve a warning by a set of manual activities.

Warnings are characterised in terms of degradation levels. For that purpose, the track condition is classified based on several parameters, e.g. geometric data. From the continuous spectrum of these parameters a discretisation into a small set of degradation levels is done. At a certain point of time a warning is at a specific degradation level. In one degradation level a certain maintenance task is necessary. Hence costs and resource requirements to resolve the warning in this degradation level are known.

From the track measurement data the current degradation level can be derived. Based on expertise and historical data a prediction for the future conditions is done by a novel predictive tool (also developed within the ACEM-Rail project). Results of this tool are the parameters of the stochastic model which are used to simulate the transition between different degradation levels. For the simulation of possible future scenarios – on which our solution approach is based on - transition probabilities are required. Therewith the development of the track condition is simulated and the influence of allocation decisions can be estimated. Furthermore these probabilities can be used to calculate the distribution of the degradation levels in the next time slots, and with it to derive expected costs, expected resource requirements, and other expected values for estimating the severity of a warning.

In the current state of the project the prediction tool is still in a development stage. To test our optimisation approach, a Markov chain is used as the stochastic model for degradation levels. Transition probabilities have been derived from railway expertise.

2.2 The Tactical Planning Process

The aim of the tactical planning is to select amongst one of the kinds of warning (basic, combined, or divided) for each predicted or existing problem on the track, and to plan the time for resolving the selected warnings in a coarse way by allocating to a time slot.

In tactical planning different aims have to be considered:

- Costs: resolve warnings by cost effective resource utilisation
- Flexibility: create a plan that can react on uncertain future developments
- Safety: resolve warnings before track enters critical conditions

Some of these aims compete against each other. For instance, a plan that resolves more warnings is more expensive. Contrariwise a low-cost plan defers more warnings and possibly resolves some of them not before a critical deterioration stage enters. To generate flexible plans track possession has to avoid as far as possible, because track possession booking leads to a fixation of warnings and therewith to a limitation of the ability to react on future development. Sometime this leads to more cost intensive plans due to the higher travel costs.

The tactical planning process is divided into two steps. At first the kind of warning (basic, combined, or divided) is selected for each problem. In the second step the chosen warnings are allocated to time slots where they will be resolved. This allocation is modelled as a Generalised Assignment Problem (GAP) [4] with stochastic costs and resource requirement. The challenge of the GAP is to find a minimum cost assignment of a set of items to a set of bins such that each item is allocated to exactly one bin. Thereby each item incurs individual costs and weights for each bin. Each bin has a given weight capacity, and the sum of the item's weights of each bin must not exceed the bin's capacity.

In order to model tactical planning as a GAP the planning horizon is subdivided into time slots (e.g. months or weeks) that represent the bins. The bin's capacities are given by the limited resources of the time slot (e.g. hours of men power, machine hours). The chosen warnings form the items. They have different costs and weights (resource requirements) in each time slot, resulting from the expected costs and resources calculated from the costs and resource requirement of the degradation levels and their probabilities.

Tactical planning is modelled as rolling process. After a given time period t_a the current plan will be adapted due to the development of track condition (progressive deterioration and occurring new problems) and extended by t_a to get a new plan covering the whole planning horizon.

3 Solution Approach: The Monte-Carlo Rollout Method

Before explaining our general approach for optimisation under uncertainties - the Monte-Carlo Rollout method - and its application to the tactical railway maintenance planning, we give a heuristic solution method to the problem. Applying this heuristic already yields to significant effects compared to conventional approaches that ignore the uncertainties in the tactical planning process.

3.1 A Heuristic Solution Method

To solve the tactical planning problem under uncertainties but without looking into the future we developed a basic heuristic **H**. Solving the tactical planning problem means to regularly adapt and extend the plan of the previous planning period to the new situation.

In **H** for each problem on the track the kind of warning is chosen that incurs the lowest average expected cost. Then within the allocation step it will be checked if it is beneficial to reallocate warnings, e.g. when the track deterioration was unforeseen or when the time slot exceeds the capacity limit. Warnings concerned are removed from the time slot and set as unallocated. Afterwards unallocated warnings are ordered by a priority considers the increase of expected costs over time and a risk factor. At last the warnings are allocated to the earliest feasible time slot according to this priority. If no feasible time slot exists, the warning stays unallocated and will be deferred to the next planning horizon.

3.2 Monte-Carlo Rollout: Basic Concept

The Monte-Carlo Rollout (MC-RO) approach combines ideas from Rollout algorithms [5] for combinatorial optimisation and the Monte-Carlo Tree Search [6] in game theory. Basic elements of the MC-RO method are a simple heuristic **H** that is capable to generate "good" solutions to the given problem based on current information, and a stochastic model for simulating the future uncertainties. Both are combined to take a look into the future and to estimate the future effects of current decisions.

The MC-RO method works as follows: Initially a set of different alternative solutions is generated. Each of these alternatives will be proven and evaluated by a number of Monte-Carlo rollouts. In each rollout a different future scenario is “played” in terms of a two-player game. Thereby the stochastic model is used to simulate random events (moves of the “random player”), and the changed situation is solved using the base heuristic **H** (moves of the “decision maker“). The two players move alternative until the end of the game or a predefined number of steps (the “depth”) is reached. The outcome of each scenario is evaluated, and the solution quality of the alternative is determined, e.g. by averaging scenario evaluations. After all the best alternative is chosen, being a high-quality solution additionally equipped with high robustness.

3.3 Application of MC-RO to the Tactical Planning Problem

In the tactical planning process the MC-RO approach is used to compare different tactical plans amongst each other. Each alternative solution is an adaption and extension of the current plan according to the new information on the track condition. By simulating different future developments of the track condition (using the stochastic model over degradation levels) the future influence of the decision is evaluated and the ability to react on different new situations is proven.

To generate the different plans we use a procedure that focusses on the selection of the kind of warning for each problem. Using the heuristic **H** the kind of warning with the lowest average costs is chosen, in contrast by generating the alternatives in the MC-RO the kind of warning is chosen randomly. In doing so, the probability of the kinds dependent on average expected costs, high costs leading to a low probability. Hence sometimes the kind of warning is chosen which is more expensive, but possibly less time intensive or more flexible in planning. All chosen warnings are allocated to the time slots as described in **H**. In this way 25 alternatives are generated. In practise this number could be increased, but in our first experiments this number showed a good trade-off between computational effort and effect of the MC-RO.

In our experiments, each alternative is proven and evaluated with 100 Monte-Carlo rollouts. Each rollout is played as a two-player game as described above. At first the random player has to move: A possible scenario for the track condition after time period t_a is generated randomly. This consists in removing all resolved warnings and randomly simulating the track condition reached after time period t_a based on the transition probabilities for degradation levels. With it the distribution of degradation levels and expected values of costs and resources have to be recalculated. At last new warnings that are supposed to occur are created randomly and added to the set of unallocated warnings. Then it is the decision maker's turn: The plan has to be adapted and extended according to the new situation. This is done by applying the base heuristic **H** to the new situation. Now the random player moves again and generates a possible scenario of the track after time period $2 \cdot t_a$. In this way the random player and the decision maker move alternatively until a given depth. (We used 12 month in our experiments).

4 First Results

The development of our solution approach for tactical planning is still ongoing work. In this section we show first results regarding the evaluation function. As described above tactical planning has different competing aims (costs, flexibility and safety), leading to a multi-objective optimisation problem. There are different methods to handle such problems [7]: the ε-Constraint method, goal programming, lexicographical order, and weighted sums.

Here three objectives have to be considered:

- C: the costs of the allocated warnings incurred and predicted
- I: the frequency of infeasibility
- U: the expected costs of unallocated warnings

All objectives have to be minimised. The frequency of infeasibility is a measure for the flexibility of the plan, and by means of the expected costs for the unallocated (and deferred) warnings we aim to express the safety aspect.

In our implementation the alternatives are tested one by one and compared with the best alternative b up to now with the evaluation values C_b, I_b and U_b (the initial best alternative is the heuristic solution). We define that alternative j (with C_j, I_j and U_j) dominates alternative b, if $I_j \leq I_b$, $C_j < C_b$ and $U_j \leq U_b \cdot (1+\alpha)$. The dominate alternative is now the best alternative b.

In our first calculation we prove the influence of α in three different instances by simulating 50 times the track deterioration for three years. Each simulation is solved with the heuristic and the MC-RO method. For each instance three graphs are pictured to show the improvement of the MC-RO method compared to the heuristic solution. The first graph pictures the improvement in the costs incurred and the second shows the improvement in the average expected costs for unallocated warnings. The improvements in infeasibility are not shown, because within the heuristic infeasible plans are rarely (under 0.5% in each instance) and within the MC-RO method all plans are feasible.

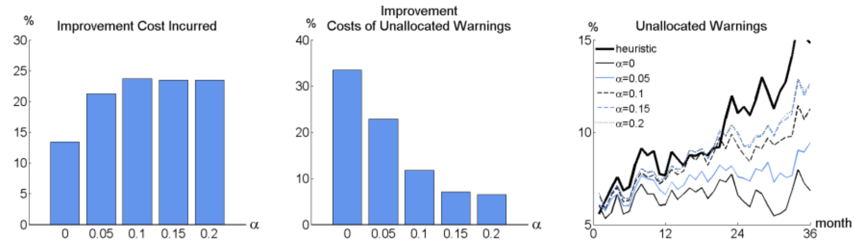

Figure 1. Results of Instance A.

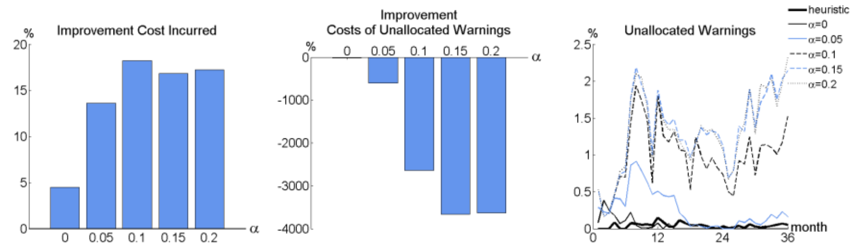

Figure 2. Results of Instance B.

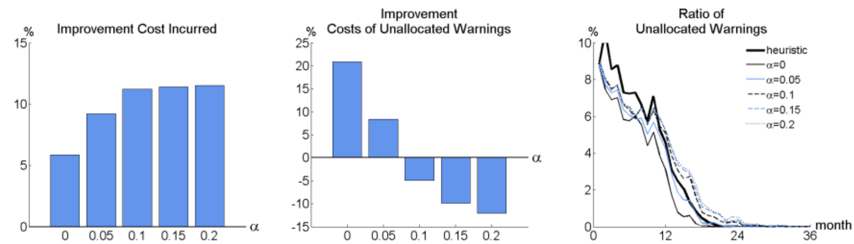

Figure 3. Results of Instance C.

In instance A the number of unallocated warnings mostly increases over time due to a tight resource capacity. As anticipated the cost improvement increases with α because of the greater range in the constraint of *U*. The improvement of the expected costs for the unallocated warnings decreases for greater α but also with α = 0.2 the MC-RO method leads to better results in *U* as the heuristic. In the third graphic the development of the unallocated warning rate is shown. Within the heuristic more and more warnings are unallocated in each plan during the three years. When solving the instance with the MC-RO method the increasing is smaller and for α = 0 the unallocated warning rate remains almost constant. Thus in instance A within all values of α an improvement in all objective can be seen. The best value is α = 0.05 because of the high improvement in *C* and *U*.

Instance B has always a low number of unallocated warnings. So the utilisation of the resources is moderate and the unallocated warnings should be not a problem. The cost improvement is lower as in instance A. Furthermore the improvement increases until α = 0.1and decreases sparse with grows α. The increasing of the expected costs for the unallocated warnings looks dramatically but is acceptable by considering the absolute values. This is illustrated by the third picture, where the unallocated warning rate is plotted over time. Within the heuristic solution and low values for α the rate is very small. And the rates for $\alpha \geq 0.1$ are still low, when comparing with instance A. Therewith the best results are obtained with $\alpha = 0.1$ because of the cost improvement is the highest.

In instance C the number of unallocated warnings is high at the beginning and decrease during the first two years to zero. The cost improvement is lower as in the other both instances. The expected costs for unallocated warnings are improved for $\alpha < 0.1$ and debased for $\alpha \geq 0.1$. So the effects of instance B recurred but not that much. Thus $\alpha = 0.1$ should be the best values because of the debasement of U is acceptable and the improvement in C reaches its maximum.

5 Conclusion

Our first results shows, we find suitable parameters for our evaluation function to generate good results. But in practice the expertise of the railway operator can be used to find the best alternative from a small set of Pareto optimal alternatives calculated and evaluated by the MC-RO method.

Our next steps are the estimation of suitable values for the number of alternatives, scenarios and the depth. Furthermore based on the long calculation time possible in practise we can increase the diversity of the alternatives and therewith the number of compared solutions. Therefor we have to expand our alternative generator.

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