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Road and Rail Infrastructure II

Stjepan Lakušić – EDITOR



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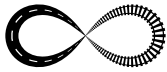
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ON A NOVEL OPTIMISATION MODEL AND SOLUTION METHOD FOR TACTICAL RAILWAY MAINTENANCE PLANNING

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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 uncertainties

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 periodic 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 and larger projects, whilst 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 during maintenance.

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 fulfilling 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 with transition probabilities from railway expertise.

2.2 The tactical planning process

The aim of the tactical planning is to select 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 are conflicting. 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 be avoided 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 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) [3] 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 weights of each bin must not exceed the bin 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 capacities are given by the limited resources of the time slot (e.g. hours of manpower, 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 tactical planning.

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 \mathcal{H} . Solving the tactical planning problem means to regularly adapt and extend the plan of the previous planning period to the new situation.

In \mathcal{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 which was planned in the last planning period, 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 which 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 [4] for combinatorial optimisation and the Monte–Carlo Tree Search [5] in game theory. Basic elements of the MC–RO method are a simple heuristic \mathcal{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 is proven and evaluated by a number of Monte–Carlo rollouts. In each rollout another 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 \mathcal{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. Each plan 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 \mathcal{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 depends on average

expected costs, high costs leading to a low probability. Hence sometimes more expensive kind of warning is chosen, 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 different plans 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 plan 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 months in our experiments.

4 First results

The development of our solution approach for tactical planning is still ongoing. 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 [6]: 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 (and deferred) warnings

All objectives have to be minimised. The costs incurred C are the costs paid for maintenance during the simulation. The frequency of infeasibility I 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 which has the evaluation values C_b , I_b and U_b (the initial best alternative is the heuristic solution). We say 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 $U_j \leq U_b \cdot (1+\alpha)$ where α is a parameter. The dominating alternative is served as the best alternative b .

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

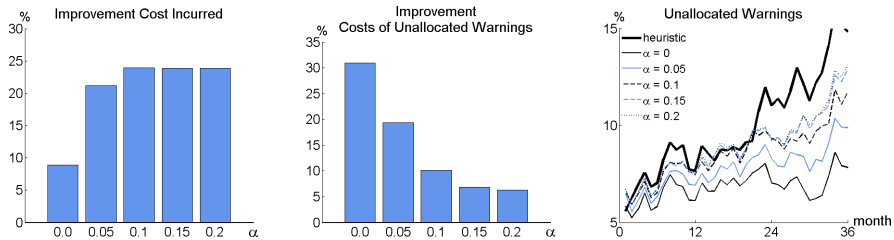


Figure 1 Results of Instance A



Figure 2 Results of Instance B

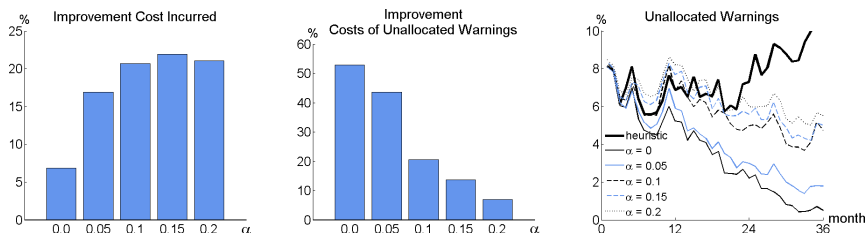


Figure 3 Results of Instance C

In instance A the number of unallocated warnings mostly increases due to a tight resource capacity. As anticipated the cost improvement increases with α because of the larger range in the constraint of u . The improvement of the expected costs for the unallocated warnings decreases for larger α but still for $\alpha = 0.2$ the MC-RO method leads to better results in u than the heuristic. 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 increase is smaller and for $\alpha = 0$ 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 for α is 0.05 because of the high improvement in c and u .

Instance B shows always a low number of unallocated warnings because of the moderate utilisation of the resources. For $\alpha = 0$ the costs improvement is very small, but this is the only value for which the expected costs for the unallocated warnings are improved. For larger α , the decline of u looks dramatically but is acceptable by considering the absolute values. This is illustrated in the third picture, where the unallocated warning rate is plotted over time. Within the heuristic solution and for low values of α , the rate is very small. And the rates are still low for $\alpha \geq 0.1$, when compared to instance A. Therewith the best results are obtained for $\alpha = 0.15$ because the cost improvement is highest. But by means of $\alpha = 0.05$ good solutions are

obtained, too. The cost improvement is indeed smaller, but the development of unallocated warnings looks better.

In instance c the number of unallocated warnings stays at a certain level during the three years. But for small $\alpha \leq 0.05$ the rate even tends to zero and is clearly better than with the heuristic. The costs improvements are similar to instance A with a preferable value of $\alpha = 0.05$, the improvement is high in the incurred costs and the costs for unallocated warnings.

5 Conclusion

Our first results show that it is possible to 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 step will be the estimation of suitable values for the number of alternatives, scenarios, and the depth. Furthermore, due to the longer calculation time that is usable in practice we even can increase the diversity of the alternatives and therewith the number of compared solutions. For this purpose we have to expand our alternative generator. Some more accurate heuristics will be also developed.

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