Optimisation of Annual Planned Rail Maintenance (Article Abstract)*

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Abstract. Research on preventative rail maintenance to date majors on small or artificial problem instances, not applicable to real-world use cases. The full article published in Computer-Aided Civil and Infrastructure Engineering tackles large, real-world rail maintenance scheduling problems. Maintenance costs and availability of the infrastructure need to be optimised, while adhering to a set of complex constraints. We develop and compare three generic approaches: an evolution strategy, a greedy meta-heuristic, and a hybrid of the two. As a case study, we schedule major preventative maintenance of a full year in the complete rail infrastructure of the Netherlands, one of the busiest rail networks of Europe. Empirical results on two real-world datasets show the hybrid approach delivers high-quality schedules.

1 Motivation

For the optimal condition of railway infrastructure it is imperative to ensure a safe and durable network, and to minimise the number of unexpected failures – causes of major disruptions to the train schedule and high costs for corrective maintenance.

The full article by Oudshoorn et al. [3] considers the case study of the Dutch railway network, which contains more than 7000 kilometres of railway track and is one of the busiest railway networks in Europe. In 2018, a total of 165 million kilometres were driven by passenger trains, and a total of 57 billion tonne-kilometres were driven by goods trains [4]. The number of trains and passengers using the network is growing annually; and the demands on the European rail network are expected to keep increasing until 2040.

Much research has been done on preventative rail maintenance scheduling [2]. However, the problems studied in the academic literature are mostly small and artificial. The methods used to solve these problems work well on small instances, but it is unclear how they would scale to a large real-world problem with complex constraints, such as exists in the Netherlands and other rail-heavy countries.

* This is an extended abstract of Oudshoorn et al. [3].

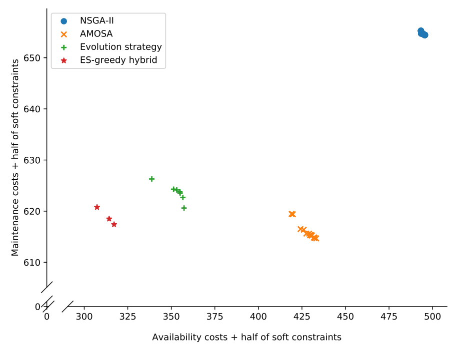

Fig. 1: Pareto frontiers between cost types, for four different methods

Algorithm	Runtime	Costs	Constraints
ProRail schedule	>6 months	965.2	690
ES, best result	24 hours	965.1	10
ES, average	24 hours	986.1	11.4
Greedy, deterministic	15 min	980.5	10
Greedy, best result	15 min	947.9	12
Hybrid, best result	24 hours	928.1	10

Table 1: Overview of results on Netherlands rail network

2 Approach and Results

Against this background, the article makes the following contributions to the state-of-the-art. First, we develop and benchmark three non-exact solution methods for the railway planned maintenance problem: an evolution strategy, a greedy algorithm, and a hybrid between these two. We provide insight into the performance of these algorithms in practice, as seen in Figure 1.

Second, we provide a study of a large-scale real-world case. The instances which come from real data require over 600 maintenance jobs to be scheduled, with more than 8000 options for each job. Further, there exist complex, non-continuous constraints which severely limit the feasible search space. This means exact methods such as mixed integer programming (MIP) solvers, which are often used to solve the indicated small instances of related problems [1], are not suitable to solve this problem.

Third, we provide solutions to a real-world national-level maintenance scheduling problem which are of better quality than the schedules currently being used, as seen in Table 1. For details, we refer to the published article.

Acknowledgements Thanks to C. Versteegt, and the CACAIE reviewers. Partially supported by TAILOR, funded by EU Horizon 2020 under grant number 952215.

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