Optimization at Deutsche Bahn AG: Aspects and Examples

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Abstract. For large transportation companies like Deutsche Bahn, process optimization has always been an important task to reduce production costs and obtain a better position in competition. Applying methods of mathematical optimization in practice often is rather difficult though, which may lead to some unique constraints that could make the optimization process rather hard. This contribution shall discuss some practical issues for mathematical optimization at Deutsche Bahn and will give some examples.

Keywords.

1 Introduction

Deutsche Bahn AG (DB) is one of the largest railway companies in Europe. With a revenue of 33.4 billion Euro [1] it would be classified in North America as class I railroad. In 2008, DB performed 78 Million passenger kilometers in public transport, and 113 billion ton kilometers in rail freight service. In addition, DB runs and maintains a network of 34,000 track kilometers which is one of the largest networks in Europe.

However, unlike other major european railway companies [2], DB has no particular optimization department where all operations research work is concentrated. Optimization projects usually take place in the operational department that is involved in the regarding field of application and that knows the considered problem well. Partners of these projects typically are optimization departments from universities or other external OR institutes. This is advantageous since many of these institutes already have railway-specific knowledge from recent projects. On the other hand there has been no specific know-how in OR methods at DB, and there are often problems to be solved with OR that are too urgent to assign an external institute with that task. In addition, there are some aspects that have to be taken into account when solving a problem for companies like DB. There are issues of management, issues of data, issues of acceptance that often play a more important role than, for instance, for smaller companies.

In the last years the spirit has changed. Due to the opening of the German rail market, cost pressure has gained more focus in operational planning while quality

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demand is still high. Also, a continuous raise of the rail freight transports are going to load the infrastructure increasingly much which leads to a higher need of construction work. For long-time predictions on traffic and infrastructure load, DB founded the department of GSU 1 which is specialized in traffic simulation and modelling including demand modelling. By this area of work, GSU 1 built a digitalized network that matches the German railway network almost perfectly. Also, the department gets all relevant traffic data for the prospects. The cost valuation also includes the simulation of the processes but it is clear that existing resource need cannot be transferred to the traffic in 2030. So GSU 1 tries to develop algorithms to simulate - and optimize - the operational planning in an abstract way but as accurate as possible. By that, GSU 1 built up optimization know-how and started several research projects with research institutes[1]. For examples of such joint projects, see [3] and [4].

The first step has been made; DB has opened for optimization methods and tries to gain advantage by them. However, there are still some obstacles to overcome, and this contribution tries to explain some of the hurdles that could occur when solving a problem with OR methods for DB. This will be done in section 2. In section 3 some examples for special constraints will be offered to show that also "standard" railway operations can be different for each railway company.

2 Practical issues of applying optimization methods

The usual way of applying optimization methods is to identify a problem you want to optimize and to decide you want so solve it with OR methods, then to build an appropiate model that describes that problem, then to find and implement an algorithm so solve that model and finally to prove that the found solution is better than the actual solution. What hurdles can show up during this process? This section is rather subjective but maybe illustrates the aspects an industry partner has in mind when launching an optimization project.

2.1 Identify a problem

For a company with so many customers like DB, it is easy to find something that is not working well. A bit (not much) more difficult is to find something not working well that you are able to change. But even if you have identified such a problem, can you solve it with mathematical optimization?

To solve problems is the main task of management. A manager decides how to solve a problem and whether to use or do not use optimization methods. If the manager is not convinced by the superiority of OR methods, he will not decide to use it. However, at DB many managers never have been in touch with mathematical optimization and therefore do not know the benefits of it - at

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least not by own experience. As an OR expert one has to be convincing that OR methods are the methods of choice. In particular, one has to take into account that time pressure is always an issue which is often a conflict to research work where you do not know in advance how the results look like.

2.2 Build a model

Now you have a problem you want so solve with OR methods. Next step is to formulate a model that describes the problem in an appropriate way. As an OR expert you usually do not know the processes in detail but rather roughly (from the manager who often does not know in detail either). Scanning the literature usually leads you to some models that were applied on that problem in history, but those typically are approximations, and every company has its own processes and restrictions. Unfortunately, those are the restrictions to be communicated at the latest - very often after presenting the first results. The devil is in the detail.

The more detailed a model, the harder it is to solve real-life instances. This is a main dilemma one have to keep in mind. Large companies like DB often have very large-scale instances that are quite a challenge for standard optimization methods, even if the problems might be researched well in literature. Decomposition techniques usually play an important role for solving optimization problems for DB.

2.3 Solve the model

When the model is set up, you are going to find and implement an algorithm to solve it. That is what an OR expert usually thinks. However, there is one step in between, that is to fill the matrix. Of course it is the responsebility of the management that all relevant data should be delivered but sometimes important data just does not exist or is not available. Estimated values often are good enough but sometimes they lead to a solution that is infeasible in practice and not locally adjustable to gain feasibility. Another point is the costs that you want to include into the objective function. For instance, the costs for a train running from station A to station B is necessary for a vehicle scheduling model but these costs depends on the total distance the train runs in a year which is actually the result of the optimization.

Coming to the actual implementation of an algorithm interests of DB and research institutes could diverge. While a research institute often has some focus on research, that is to find new algorithms or solution methods, DB wants good solutions quickly, no matter what methods (e.g. heuristics, standard solver) has been applied. The

2.4 Competition to actual solution

Once the problem is solved and you have a solution that is optimal according to the objective function and the constraints, you have to prove that it is better than the actual solution. Despite the optimality, this is not obvious. The the reality is not mapped 1-to-1 onto the model; there are always constraints and details you had to omit for complexity reasons.

In operations at DB, many plans are made manually. The planners have been planning and designing lines, schedules, trains, networks for many years and thus they know the problem structure very well. And they are very good at adjusting an existing plan and making local improvements since the annual changes are often rather small. So probably the planners offer a solution that is feasible and has a reasonably good value, while your solution might have a better solution value but is feasible only in the abstract model. To give an actual proof you have to run a pilot project to check whether the abstraction of the model is reasonable.

3 Examples

In this section we will give two examples for special constraints occuring in well-kown optimization problems at DB. These constraints lead to special variants of the responding problems on which existing solution methods and modelling techniques can not be applied directly but must be modified or remodeled.

3.1 Homogeneous Schedules

The task of vehicle scheduling is to assign a vehicle (locomotive) to each trip of a given timetable. This problem is well known and there are many contributions (see [5], [6], [7] for instance). Usually, this problem is modelled and solved as an assignment problem or a (multicommodity) flow problem. Either way, all trips are considered locally, i.e. the assignment of one trip does not change the constraints on other trips. However, in practice trips are planned differently which leads to a different view of the schedule, a view the planners are used to and that can not be offered using a common optimization technique.

How does this work in particular? Trips are often performed on different days but on the same time with the same origin and destination. Those trips are grouped together to a *train*. Connecting two trains means that the regarding trips are connected at every day both trips are performed (that is, after performing the first trip a vehicle performs the second). The *distance* $d(N_1, N_2)$ between two trips N_1, N_2 of a train is measured in days. So if N_1 is performed on tuesday and N_2 is performed on monday, the distance $d(N_1, N_2)$ is six days. A sequence of connected trips is called a *chain*.

We now introduce homogeneous schedules, a concept that turns out to be important for planners in vehicle scheduling.

Definition 1. *A schedule is called* homogeneous *if the following holds: let N_1, N_2 be trips of a train N and N_1^*, N_2^* be trips of a train N^* with $d(N_1, N_2) = d(N_1^*, N_2^*)$. Let C be a chain from N_1 to N_1^*. Then there exists a chain C^* from N_2 to N_2^* of the same length (measured in days) as C.*

It is one objective in vehicle scheduling to create plans as homogeneous as possible. The reason is that a weekly schedule can be displayed as one day even if connections between trains sometimes differ from day to day. Not only the planners are most familiar with this particular view but also the planning software of DB includes this concept.

A completely homogeneous schedule is always possible and feasible, it is not optimal regarding vehicle and deadhead costs though. It is also less important than vehicle and deadhead costs, thus the question is how to find a solution that is optimal regarding vehicle and deadhead costs and that is as homogeneous as possible. It is part of a current research project of DB to integrate the concept of trains and homogeneity in vehicle scheduling [8].

3.2 Leitwege

Another special constraint occurs during routing cars in rail freight service. Sending shipments of small size (measured in cars) from origin to destination you usually send them to a near shunting yard where cars with the same destination are combined to a train. After arriving at the next intermediate yard the cars might be recombined with other cars to new trains until they reach their destination. This problem can be modelled as a multicommodity-flow-problem. At DB, you have an additional constraint: whenever two shipments with the same destination reach an intermediate yard the path to the destination must be the same for both shipments. When costs are linear in capacitated trains this constraint could cut off the optimal routing (see [9] for an example). The reasons for this constraint are not technical but rather operational. When a car arrives at a yard no more information but the destination is needed. This makes the system less accident-sensitive. Also, this routing system provides a simple rule of the form (actual yard—destination yard—next yard) which is included in the planning software. Therefore the Leitwege-constraint is obligatory unless you do not change the whole IT-system (that is similar to the situation in section 3.1).

Finding optimal routes for cars in rail freight transport is a research project of DB and University of Technology Darmstadt (for more information see [4]).

4 Conclusions

The aspects subjectively mentioned in section 2 all seem to be rather of disadvantage and deliberately there are no "solutions" given since the departments at DB differ a lot. This is not meant to be discouraging but as part of preparation for situations that could occur when starting an optimization project with DB. However, times change and departments like GSU 1 offer a more inviting environment for operations research including operational and optimization know-how and a huge database with relevant data. The examples in section 3 show that solutions developed at other railroads or institutes are not always applicable at DB, and that is why there are many fields of research to attend to and DB is a company with a huge demand for OR.

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