Visual Analytics for Supporting Conflict Resolution in Large Railway Networks

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Abstract. Train operators are responsible for maintaining and following the schedule of large-scale railway transport systems. Disruptions to this schedule imply conflicts that occur when two trains are bound to use the same railway segment. It is upon the train operator to decide which train must go first to resolve the conflict. As the railway transport system is a large and complex network, the decision may have a high impact on the future schedule, further train delay, costs, and other performance indicators. Due to this complexity and the enormous amount of underlying data, machine learning models have proven to be useful. However, the automated models are not accessible to the train operators which results in a low trust in following their predictions. We propose a Visual Analytics solution for a decision support system to support the train operators in making an informed decision while providing access to the complex machine learning models. Different integrated, interactive views allow the train operator to explore the various impacts that a decision may have. Additionally, the user can compare various data-driven models which are structured by an experience-based model. We demonstrate a decision-making process in a use case highlighting how the different views are made use of by the train operator.

Keywords: Visual and Big Data Analytics · Decision Support Systems.

1 Introduction

Railway Transport Systems (RTSs) play a crucial role in servicing the global society and the transport backbone of a sustainable economy. A well functioning RTS should meet the requirements defined in the form of the 7R formula [16, 13]: *Right Product, Right Quantity, Right Quality, Right Place, Right Time, Right Customer,* and *Right Price*. Therefore, an RTS should provide: (i) availability of appropriate products (the provisioning of different categories of train), (ii) proper number of executed transportation tasks (enough trains to fulfill the request), (iii) proper quality of execution of transportation tasks (safety, correct scheduling, and effective conflicts resolution), (iv) right place of destination according to a timetable (correct transportation routes), (v) appropriate lead time (reduced *train delays*), (vi) appropriate recipients (focused on different customer needs and requirements), and (vii) appropriate price (both from the point of view of the customers and the infrastructure managers).

The main responsibility of a train operator (TO) is to ensure the safety and smooth running of the trains and their scheduling. Although there exists a given train schedule, the TOs have to deal with derivations caused by delays, defects, or other unexpected impacting events. A conflict occurs when, due to the aforementioned reasons, regularly scheduled trains are delayed so that they would utilize the same railway-segment at the same time. Although this poses no immediate danger as the interlocking system will not allow both trains to drive, however, the operator must decide which train can go first. This decision is critical from the point of view that the criteria of the 7R formula should be respected. In the current state-of-the-art, a rule-based system proposes a solution on which train should go first. Yet, since the decision is not expla In fact, the TOs mostly rely on their experience because most conflicts happen regularly, e.g., every day at the same time with the same two trains involved, as the schedule is mostly the same each day, and thus, vulnerable to the same challenges. This makes it difficult for TOs that lack experience to choose the optimal decision. This is also true for operators when they operate another region. Lastly, there is a risk that the selected decision of the TO is actually not optimal due to impacting cognitive biases such as the confirmation bias [1].

Dedicated Machine Learning (ML) techniques exist to predict the behavior of Large-Scale RTSs [15]. Such models are well suited to support the train operator in their decision-making process for conflict resolution. While their accuracy is convincing, the TOs have a rather hesitant stance towards these ML models as they typically do not reveal their inner workings nor explain why a specific decision on which train (A or B) should go first is recommended as superior to the second option. Visual Analytics (VA) has proven to be effective to overcome this boundary [18]. VA is a multi-disciplinary field which combines methods from machine learning, visualization, human perception, and human-computer interaction to support the useful understanding, reasoning, and decision making.

We propose a Visual Analytics Decision Support System (VADSS) for train operators that embeds these powerful ML models while providing access to the models through VA. This helps the TOs to make an informed decision whereas their experience is directly encoded into the system and not only resides in the operators' minds. We call this the *stateless operator*. By taking the operator's experience directly into the system, experience can be shared and pitfalls of knowledge only present in the operator's mind, such as misremembering, are mitigated. We identify four main aspects that are necessary for the TO to choose the optimal decision effectively. First, the complexity of the network and the manifold factors require an automatic model that optimizes on these various metrics. The TO needs to be able to inspect the models and the metrics on what these models optimize and must be able to compare this. Secondly, the TO needs to understand how the automatic models derive their decisions. Therefore, a model visualization is necessary. Thirdly, the impact of either decision (train A or B) must be visualized in the schedule visualization such that the impact on singular events or trains becomes visible which may be of higher priority than a global metric. Lastly, the historical decisions on the respective conflict must be available and accessible to the TO and must convey the historic information of the model and its predicted metrics, the actual metrics, as well as the impact of the decision to the schedule.

The proposed VADSS combines and integrates all these aspects. The next Section covers the first to aspects of the system and details which models are used to predict states and variables for large train networks. In Section 3, the combined system is described and also the second, third and fourth aspect of the systems are detailed. Furthermore, a use-case in Section 4 describes the decision making process and highlights the various aspects of the system. Section 5 draws some conclusions and outlines further research aspects.

2 Prediction Models for Large Train Networks

Train management systems can have a large number of different possible models to use to predict which decision in a critical case should be used or advised. First, there are Experience-Based Models (EBMs) [7] [6], which are often generated out of rules from a train network and the experience of a train operator. Such models are often rule-based or based on decision trees (DT). Second, Data-Driven Models (DDMs) [14], which are created out of the historical data for the critical case. DDMs can be arbitrary machine learning models, such as random forests (RF) [3], Extreme Learning Machine (ELM) [8] or others. To be able to achieve the best of both worlds, Lulli et al. [12] propose a Hybrid Model (HM) incorporating the knowledge of the EBM to select an appropriate DDM. However, due to the nature of the task, it is necessary that a user can understand the decision basis of every model in a few seconds or minutes. Such complex decision models require the use of visual analytics to make them accessible to the train operators such that the visualizations highlight the important aspects of the model.

Through the nature of the proposed HM system by Lulli et al. [12], these visualization concepts focus on the decision making of a DT at first and more difficult algorithms later. By design, DTs are more understandable but can get quite complicated if the data which they are trained on is high-dimensional and complex. Highlighting a decision path through the first part of a HM to select a DDM is essential to show the user on which basis the first stage EBM decides for an underlying second stage DDM. This decision path can help a user to understand if the correct model was taken or if some other factors are weighted heavier than others. Features such as *railway section, railway checkpoint, train type, daytime, weekday, last delay and weather conditions* are just a few on which the decision for a DDM is made by the EBM. The feature-based reasoning of which DDM is chosen by the EBM significantly impacts the understanding of what priorities the DDM will have to base its prediction on.

A solution to this issue is to show a visualization of the DT that represents the EBM and to highlight the path the model took to choose a DDM. Through the visualization it is intuitive to understand what features are selected for the later prediction. For instance, the model could have chosen the *weekday* and the *daytime* to select a model and neglected the other features because in the case of the rush hour these are the essential features. Also, some outlier cases in which the DT takes a wrong turn could be identified. It could be that a DDM is chosen based on some path, which is not ideal, e.g. in a rush hour instead of *weekday* and *daytime*, *last delay* and *weather conditions*. A train operator can identify and fix it quickly with her experience and domain knowledge.

To further include the decisions of the underlying and possibly chosen DDM, the results of an explanation method are displayed. In the case of the HM, the chosen second stage DDM is a random forest and has its own feature set. The features for the RF are *weather information, past train delays, past dwell times, past running times, network congestion and network congestion delays.* Only visualizing all the DT of an RF is not sufficient as an RF in most cases consists of too many trees to show in limited space and due to their design as weak classifiers they are only useful in combination. There are, to some extend, methods to visualize RFs, for example, Forest Floor [19]. However, this method is difficult to interpret in a short time and requires a profound knowledge of the general technique to understand the decision the model suggests. A possible explanation method for an RF without a visualization would be to show the variable importance [3]. The variable importance of RFs show which features are most often used as a split criterion and thus more descriptive to separate and predict the data. For instance, the more often a feature such as *network congestion* is chosen as a split, the more descriptive this feature is to the dataset. To enable a fast understanding of the train operator, the system only shows the top three features in text ranked by importance, and some of the underlying information is hidden.

Other Machine Learning techniques, which are for instance in the proposed ELM by Oneto et al. [15], also have some possibilities to show such feature importance in a short, summarized way. In the case of an ELM, which is a type of a Neural Network, extracting an explanation is challenging due to its complexity but can be achieved through explanation methods such as LIME [17]. In general, showing the decision process of an algorithm, is a crucial part to build the train operators trust into the proposed decision and the model in general. Trust into the automated processes of a system is essential for the effective usage of the system [11]. While explaining and understanding the general approach of a model is crucial [9], visualization *is* required - especially for decision processes.

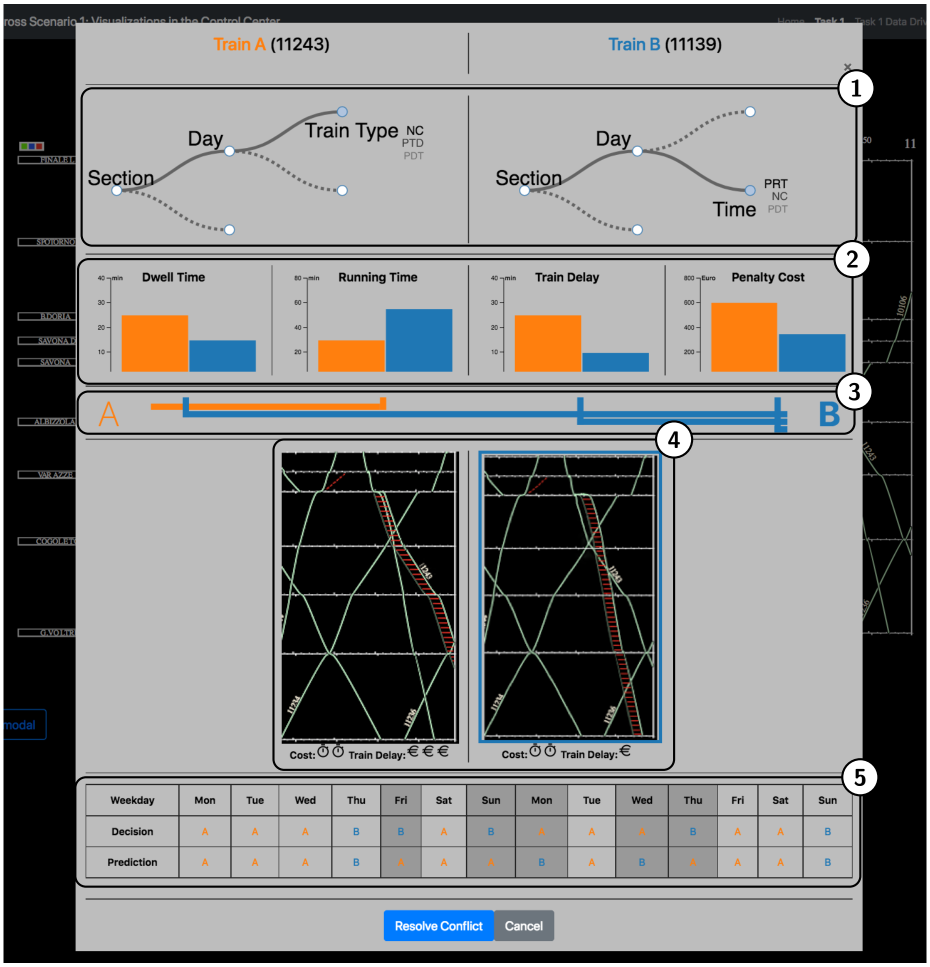

Fig. 1. Integrated view on the proposed conflict resolution interface containing the reduced complexity model view (1), the metrics comparison view (2), the pipeline visualization (3), the side-by-side schedule prediction visualization (4) and the Historical overview on previous decisions (5).

3 Visual Analytics Decision Support System

The interactive visual exploration of prediction models and the predictions themselves are essential for an operator to further learn about the impact of her decision. Therefore, our primary goal is to present the operator interpretable models and their results to gain insight for solving train conflicts. We propose the Visual Analytics Decision Support prototype (see Figure 1) which visualizes the hybrid model as introduced in Section 2, the resulting costs, a visual preview of the two predicted train schedules, and the experience-based data.

Our proposed Visual Analytics prototype supports proactive decision making, enabling the train management operator to investigate and assess decisions, to find optimal solutions, and to minimize risks. To achieve this goal, we extend existing visualizations in the control room setup following the VA principle introduced by Keim et al. [10].

In our work, we build upon Train Delay Prediction Systems (TDPS) as proposed by Oneto et al. [15]. TDPS can have different optimization strategies and rescheduling predictions, optimizing for different features and strategies such as experience driven [15], energy-efficient railway operations [2], passenger reliability perception [5], delay in the system [4] or others. The proposed hybrid model [15] combines EBMs and DDMs that are already in use by the RFI. In collaboration with the RFI experts, we have designed and implemented two views (see Figure 1) to explore the HM and the resulting costs visually.

With our proposed solution, we intend to bridge the gap between model exploration and decision-making in a safety-critical environment. Bringing together Model and Solution Space Visualization at an operator's workstation entails careful consideration of the amount of information presented as well as the complexity of the provided interaction functionality. According to TMS experts, typically, operators consider only a narrow time frame of about 30 minutes after an occurring conflict to survey the results of the decisions they take. Any complications beyond this time frame is not considered due to the increasing complexity coming with each additional affected train.

Consequently, interfaces need to be minimalist in the amount of displayed information, yet able to always provide the right information, also dynamically, to an expert at the right time in the right granularity to rapidly make informed decisions and achieve the *stateless operator*. We determine four main components required for a rapid decision making interface for conflict resolution:
(1) Reduced-Complexity Model Representation
(2) Metrics comparison view
(3) Pipeline visualization for statistics exploration
(4) Side-by-side schedule prediction view
(5) Historical overview on previous decisions

Having an insight into the prediction model as discussed in Section 2 is essential for an operator to decide whether or not the model factors in all aspects the operator deems important. In other words, the visualization allows operators to decide, whether they should *trust* the model or not. The first view (see Figure 1 (1)) in our Visual Analytics prototype shows the EBMs that capture the knowledge of senior operators in the form of a DT. The two DT visualizations enable to identify, why a specific DDM was chosen by the EBM. Additionally, the operator can interactively explore alternative branches in both DTs by selecting decision nodes. The features of the EBM (e.g., railway section and train type) are included in the view to foster the interpretablity of the model.

The visualization also enables to investigate the input features (hovering the root node) and shows only the highlighted decision path. We enable the exploration of the EBM to see why a specific DDM was chosen. The train operator can use a mouseover to investigate the decision path with all branching condition to understand the result of the EBM. Furthermore, next to the leaf nodes, we show the three specific features that are weighted important by the DDM. By displaying the feature importance, the operator is able to identify the most important features for the decision of the DDM. The operator is able to explore alternative branches in the DT by selecting nodes.

The second visualization (see Figure 1 (2)) displays the predicted resulting costs of both selected DDMs (e.g., running time and the dwell time). We linked the second view to the selection of the selected DDMs in the DT visualization. The results are shown in grouped bar charts enabling an intuitive comparison of the resulting cost of the two train predictions. By directly comparing the costs and the alternative path selections in the DT, we aim to help the operator to understand the HM, the predicted costs, and the trade-offs between them. Furthermore, the operator can look at alternative DDMs and include them in his decision. To improve the rapid interpretability of the confronted statistics, the pipeline visualization (see Figure 1 (3)) connects a line from the "winning side" for each feature to the respective train (either A or B).

Having selected the appropriate model, the third part of our proposed solution (see Figure 1 (4)) allows comparing the outcome of the two options the operator can choose from, namely which of the two trains A and B is allowed to move on first. For each of the two scenarios, the projected outcome is visualized in the same style as for the general schedule in the background. The red-shaded area indicates the consequence and deviation to the schedule if the operator decides for this solution. In addition, the main differences between the two models are expressed using an icon-based, simplified approximation, here at the example of cost and time. The predicted cost and delay time are binned to a simple representation of intuitive icons such as currency symbol and a clock. For each feature, one to five icons represent low to high cost or overall delay introduced through the decision.

At times it is possible that, despite the ability to explore and select the applied model, the expectation of the operator still differs from the proposed solution. As well, operators new on the job or the respective region or temporary replacements might have not yet enough experience to make informed decisions. To support our concept of the *stateless operator*, the last part of our suggested view provides a historical overview on previous similar situations and how they were decided. The user can see, what the model has predicted as the best solution versus which solution was finally picked by the operator. The overview on recorded decisions is suitable to either, ideally, reinforce the trust of the operator in the models or to hint at bad model quality depending on how many decisions have been met in accordance with the model in the past.

Our proposed visualization enables the train management operator to assess and evaluate the prediction model results to understand alternative solutions and impact on the train schedule. Furthermore, the visualization of the predicted costs enables the train management operator to gain knowledge about the uncertainty in the prediction. Supported by a clear global color-coding, the operator is now able to make an informed decision for conflict resolution. We do not expect operators to make use of all views for every decision, but instead to adapt the applied models to current operating conditions. On a more general level, the system is also intended to create more trust for the provided models, which, according to our experts, is improvable due to the currently applied black-box model representations presented to the operators.

4 Use Cases

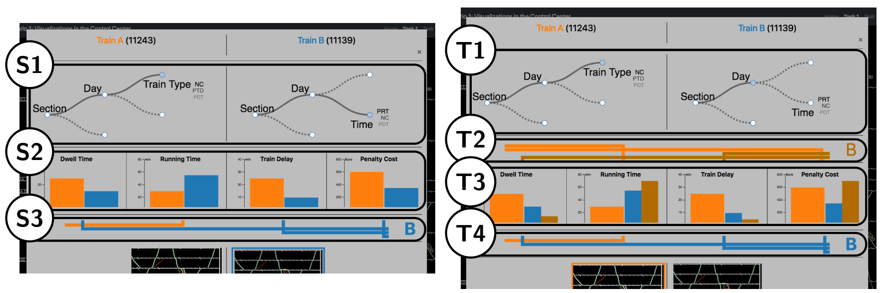

Fig. 2. (S1-3) shows a critical conflict with the model predictions and information. (T1-4) shows another third model selected by the user to incorporate into the decision of the TO.

To show how an operator is able to interact with the system, this section provides a use case scenario to show a step by step process of a TO. The task consists of a critical conflict emerging if two trains need to leave or arrive at a station at the same time, while there is no rail for both of them available. The TO has to decide which train should have priority and solve the critical conflict. As described before, a decision can have a rather big influence on the train network and schedule overall. The TO wants to minimize the *penalty cost* at all times, while still be able to have a low *train delay*.

When a conflict emerges, the system notifies the TO by showing her or him a new modal with the relevant information described in previous sections. Either train A or train B should have priority in a conflict to solve it. The HM in Figure 2 (S1-3) shows a lower *penalty cost* for train B and thus advises the TO to choose it. This lower *penalty cost* can either be seen in (S2) and the lower bar in the metric comparison view or in (S3) in the pipeline visualization, which clearly favors train B. However, as the TO wants to further investigate and understand the decision, he inspects the visualizations of the available information. This inspection means he takes a look at the DT visualization and the important features for the RF prediction at (S1). With the decision process of the DT in mind and the features of the RF, he decides that the *penalty cost* estimation makes sense and that the model is correct. The TO decides to give train B priority to solve the conflict.

However, in another scenario Figure 2 (T1-4), the TO could possibly be not satisfied with the model decisions. He thinks it is not advisable in the DT to use some of the features for a decision making. Other features are better for this specific case of solving the conflict, judging by his experience. In this case, the TO chooses another branch in the DT (T1) to take another DDM into account, which uses the data the operator thinks fits this situation and train better. This other DDM shows that after changing the model the other train has a higher *penalty cost* in the bar char and pipeline visualizations (T2-3). He can still compare how the different models decided in (T3) and by comparing the two pipelines in (T2) and (T4). Train A shows a better performance and the operator should pick it in this case.

5 Conclusion

Train operators constantly have to decide which train can go first in case of a conflict. Their decisions impact the schedule of large-scale railway transport systems and the associated performance metrics such as train delay and penalty cost. We present an integrated view for conflict resolution that makes use of the Hybrid Model proposed by Lulli et al. [12]. Our composed view provides train operators access to these models leveraging their power and increasing the user's trust into these models. The train operators are further enabled to explore a variety of models which are selected by an experience-based model. The train operators can explore what performance metrics are predicted by the different models. A Pipeline Visualization aids the train operators in how the various predicted metrics impact the current data-driven prediction for the decision. Furthermore, they can see how the future schedule will be impacted. A historical view shows past decisions of the operator in conjunction with the predicted decisions of the data-driven models. This supports the user to spot temporal and periodic patterns and shows if, for a particular conflict, train operators followed the proposition of the automated model. A use-case demonstrates how a train operator interacts with the integrated view to formulate her decision.

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