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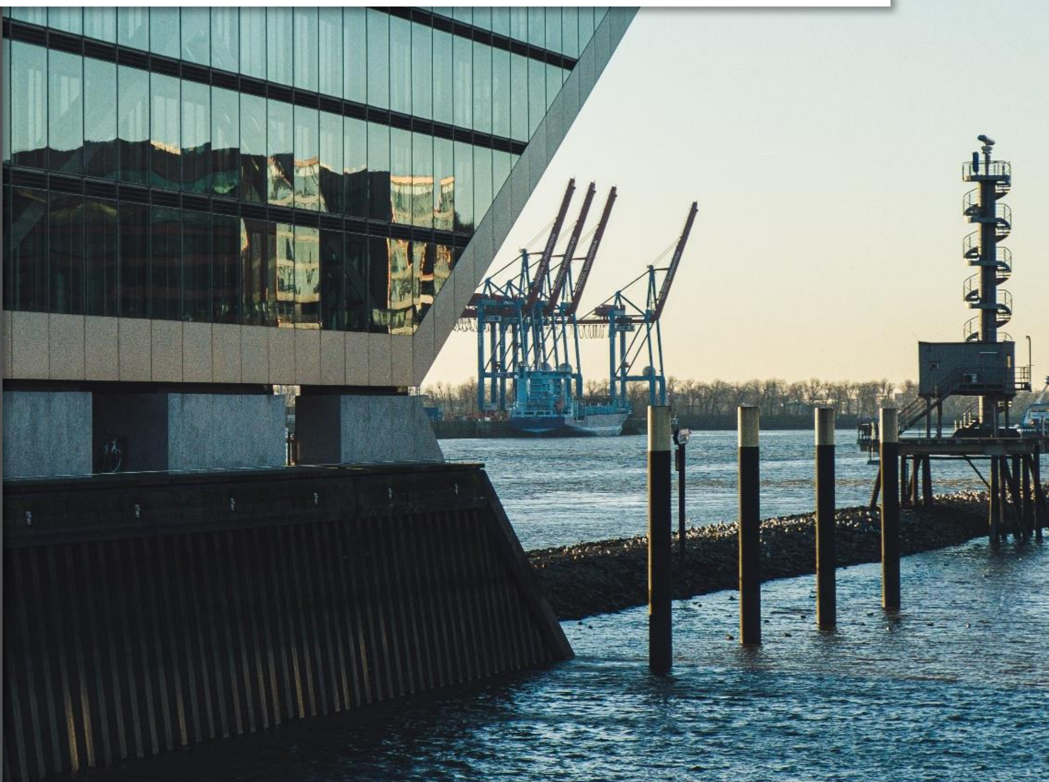

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Decision-making in Multimodal Supply Chains using Machine Learning

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Purpose: *To strengthen efficiency and resilience of supply chains at the same time, shippers and logistics companies needs proactive transparency about their orders. Machine Learning (ML) offers huge potential for precise predictions of complex logistics processes. This paper shows the results of a perennial research for implementing a ML-based system, which predicts multimodal supply chains, detects upcoming disruptions and provides suitable actor-specific measures.*

Methodology: *For each process of the considered supply chain an individual prediction model is developed, using four years historical data, about 50 identified features and various ML methods. The developed cross-actor ETA was linked with preventive measures based on expert knowledge. Both was integrated into a web-based prototype of a self-learning decision support system.*

Findings: *Thanks to the development of different ML approaches, most reliable model configurations were identified for each process. Moreover, important insights were gained regarding the availability of required data as well as the potentials and challenges of using ML-based solutions for decision-making processes in logistics.*

Originality: *The potentials from the use of ML for predicting supply chains has only been carried out for particular processes. An integrated approach including different processes like rail transports and transshipment points as well as a linkage with prediction-based measures is still missing.*

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1 Introduction

Increasing demands on the reliability, flexibility and efficiency of logistics services require companies to make fast and optimal decisions when planning and controlling their supply chains (SC) (Handfield, et al., 2013). In this context, logistics decision-makers are faced with complex problems. A large number of influencing factors are present, which are continuously changing. In addition, various objectives corresponding to the different logistics stakeholders have to be considered, which are partly in conflict with each other (Straube, 2004). Many of the decisions are conducted under uncertainty, since often not all information is accessible.

One essential process information for Supply Chain Management (SCM) is the Estimated Time of Arrival (ETA) of the respective goods at various points in order to synchronize the individual processes and to ensure a demand-oriented capacity planning with regard to material stocks, personnel and infrastructure (Walter, 2015). The dynamic and diverse influences on process execution do not yet allow reliable predictions of the respective SC progressions (Weinke, et al., 2018). The difficulty of estimating process or arrival times applies in particular to multi-stage SC, due to the complex interdependencies of their individual process stages, as in the case of multimodal transports. This lack of transparency means that, currently only reactive action can be taken in response to disruptive events that occur. The derived decisions to adapt the processes often do not represent an optimum with regard to the overall SC. This results in high economic and ecological disadvantages for global SC in the form of unpunctual deliveries, underutilized transports, cost-intensive exception processes, and unnecessary risk buffers, which are shown in Figure 1 (Poschmann, et al., 2019).

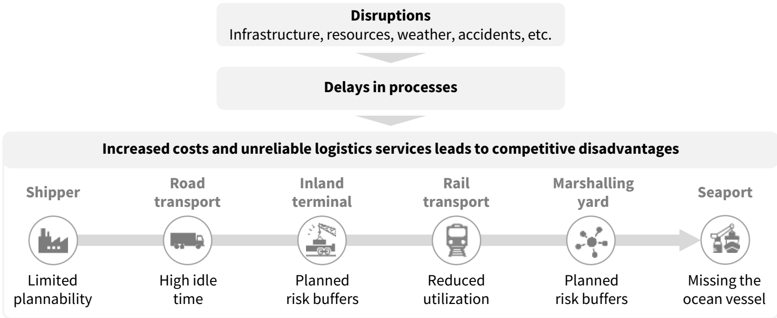

Figure 1: Effects of disruptions in multimodal supply chains

The use of Machine Learning (ML) to address this complexity in SC decision-making processes has high potential (BVL, 2018; Jordan and Mitchell, 2015; Straube, et al., 2020). With the help of self-learning IT-systems, problems can be solved more flexibly, with less effort, and with a higher accuracy of results. Moreover, it is the ability of systems to learn that enables autonomous execution of processes (Wahlster, 2017).

This paper investigates the feasibility of ML for predicting multimodal SC. Therefore, it shows the development of a prototypical IT-system, which for the first time uses ML for calculating ETA in this context and provides the involved actors with measures based on these predictions for a proactive avoidance of identified disruptions. In the following sections the procedure and main results of a three-year research process to develop this self-learning decision support system are presented. At the beginning, the framework of the project is discussed with a brief overview of the application area, the ML technology and previous approaches for predicting multimodal SC. Subsequently, the methodology of the development process is described. According to the individual steps, several results are presented, e.g. on the considered data and features as well as on the developed ML models for the ETA prediction and the corresponding expert-system for prediction-based measures. Afterwards, the implications for research and practice are critically reviewed. The last section provides a summary of the paper and an outlook for corresponding activities.

The paper addresses practitioners, such as logistics companies and shippers, as well as future research projects, which want to implement a ML-based decision support system in the context of process predictions. Information that may be used includes potentials of ETA for SCM, data availability, relevant features, suitable ML models for several SC processes and their reasonable integration, as well as the linkage of symbolic and sub-symbolic AI approaches.

2 Framework

2.1 Application area

The use-case of this paper is the combined transport (CT) of rail and road in the pre-carriage of the maritime SC. Therefore, real customer orders of sea freight containers from industrial shippers to the seaport were considered. In the corresponding door-to-port process chain, a container is picked up at the shipper and is first delivered by a truck to an inland terminal. Within this logistics node a potential short-term storage as well as a transshipment to a train is conducted. The according hinterland train is moving to a marshalling yard (MY), possibly with several stops for changing crews, traction units and wagons. In the MY, the respective wagon is partially again buffered for a short-time and transferred to a feeder train, which goes to the designated container terminal in the seaport. This considered process chain in the project is followed by a main leg with an ocean vessel and by a landside subsequent leg, which ends with the delivery of the container at the customer. This fragmentation of the process chain also leads to the involvement of various container-carrying and overarching actors, which are all potential owners of required data (Poschmann, et al., 2019). These include trucking companies, terminal operators in the inland and seaport, railway undertakings (RU) including marshalling companies, as well as infrastructure operators, CT operators, freight forwarders and shipping lines.

2.2 Machine Learning

ML is a subfield of Artificial Intelligence (AI) and combines several technical approaches, which can be broadly categorized into the three main types of supervised, unsupervised and reinforcement learning (Russell and Norvig, 2010). In contrast to a manual coding by rules or ontologies, which represent the knowledge of previous IT-systems for solving problems, in ML empirical relationships are determined independently by algorithms (Murphy, 2012). For this purpose, this sub-symbolic approach uses data on the respective domain as a basis for learning (Alpaydın, 2010). By evaluating the obtained results against a predefined performance metric, the ML approach allows for continuous improvement, i.e. a steadily more effective and efficient accomplishment of the considered task (Simon, 1983). This automatic acquisition of knowledge about the application area enables the recognition of complex correlations for problem-solving, which are not recognizable to humans or only with great effort. These patterns can be used for various operational tasks, including segmenting objects, deriving rules, determining future values in the form of predictions, and determining optimal solutions, including creating new content (Alpaydın, 2010; Döbel, et al., 2018).

2.3 Prediction of multimodal supply chains

For the evaluation of the state of research, an analysis of previous literature was conducted. Its results on existing prediction solutions of process or arrival times in multimodal SC are presented in this section. They were used for the initial evaluation of the suitability of prediction methods. Basically, a distinction can be made between model-based approaches, which are mostly based on simulation, and data-based approaches (Wen, et al., 2017). Approaches based on ML can be seen as a subset of data-based approaches, which were the focus of the literature review. Solutions for the entire SC as well as for the individual subprocesses were included.

The only representative for ML-based predictions of multimodal SC was identified as the paper by Servos, et al. (2020), in which an approach for ETA prediction for container transports over the maritime SC is developed. Randomized trees, adaptive boosting, and support vector machines (SVM) are used. The approach only incorporates GPS data, but no other data, so operational factors influencing arrival time are not covered.

The availability of approaches for specific subprocesses depends heavily on the transport mode. For the main leg by ocean vessels, initial approaches to ETA prediction already exist. For example, in Lechtenberg, et al. (2019) an approach for the prediction of arrival times for ocean vessels in specific destination port regions is developed. For this purpose, different ML methods such as artificial neural networks (ANN), SVM, and gradient boosting are tested. For the road freight, hardly any scientific elaborations could be identified so far. Existing work focused on passenger traffic arrival time prediction, such as the paper of Fan and Gurmu (2015), which i.a. used ANN to predict travel times of buses. These are not directly transferable to freight transports. Only Li and Bai (2016) consider the development of an approach for road freight using gradient boosting, which includes only temporal characteristics. In case of rail, only data-based approaches exist for passenger transport. For example, Yaghini, et al. (2013) developed a prediction for passenger trains using ANN and decision trees. Markovic, et al. (2015) predict passenger train delay using ANN and SVM. Due to the different operational framework, these approaches are not directly transferable to freight transport. No paper on data-based approaches has yet been identified for relevant logistical nodes of inland terminals and marshalling yards.

In summary, there are currently hardly any reliable solutions for a data-based cross-process prediction of multimodal SC. This also applies to the individual subprocesses. Due to the high effort of mapping complex problems and the low scalability, model-based approaches have only established for individual subproblems, e.g. the modeling of subsequent delays in rail transport, but not for more complex multimodal systems. Instead, manual calculation methods based on subjective experiences of the process participants or extrapolations of current delay based on tracking information continue to dominate in this application area.

3 Methodology

To cover as wide a range of requirements and data, various companies were involved in the project, covering the individual actor roles in the considered SC, including shippers, terminal and infrastructure operators, land and sea carriers as well as CT operators and freight forwarders. The procedure was based on the industry-wide standard for planning of data-based projects in the form of the CRISP-DM. Based on an examination of the problem, this model provides an iterative procedure for the analysis and preparation of data as well as several steps for model development (Wirth and Hipp, 2000). According to the objectives, this procedure was adapted for the project (see Figure 2) and is described in this section according to several phases.

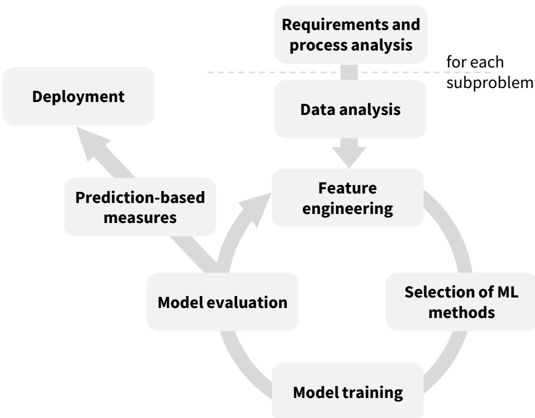

Figure 2: Structure of the research procedure

Requirements and process analysis: In order to realize a practice-oriented solution, the first step was to record and evaluate the requirements of the actors as well as the potential of the targeted solution. Together with the process-owners, important disruptions and their causes in multimodal SC were elaborated. Based on these activities, a specification of the application area for the development process was conducted, including the selection of suitable pilot relations and the segmentation into different subprocesses based on data-side and operational requirements. Within these activities, 16 expert-interviews with a subsequent written survey were conducted.

Data analysis: The availability of historical data was an essential prerequisite for the targeted ML approach. Therefore, different measures were pursued to obtain appropriate data sources for each subprocess. The acquired data was processed and analyzed. This included both the consideration of process characteristics and the identification of possible factors, which are influencing process times. For this purpose, data visualization and methods for investigating correlations from the field of unsupervised learning were used.

Feature engineering: Based on the identified influencing factors and their causes, suitable input variables (features) were determined for all subproblems of the prediction. On the one hand, directly existing variables from the data sets were used as features. On the other hand, new variables were constructed by combining and transforming one or more existing variables.

Selection of ML methods: Based on these findings, potentially suitable ML methods from the field of supervised learning were selected for the specific problems. Among others., the type of target variable (classification or regression) and input variables, the statistical correlations between them, and the available training data and its quality were considered.

Model Training: The selected ML methods were finally trained for each subproblem with historical training data, whereby different model configurations were tested. Grid Search methods were used to determine the hyperparameters using a 10-fold cross validation for each subproblem.

Model evaluation: To determine the achievable prediction quality of the respective trained models, these were applied to an independent test data set. The MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error) for regression problems and the accuracy for classification problems were used as quality measures. In addition, further problem-specific metrics were calculated for better external comprehension.

Prediction-based measures: Together with the actors, ETA-based use-cases and corresponding measures were investigated with regards to potential inefficiencies and disruptions for the individual processes along the SC. These optimization opportunities were evaluated with regard to various criteria. Further six expert-interviews were conducted. Subsequently, selected results were transferred into a rule-based logic in the form of an expert-system. By this symbolic AI approach, knowledge and reasoning ability of human experts on a specific domain are emulated (Beierle and Kern-Isberner, 2019). In this case, the system should automatically detect disruptions and provide recommendations for optimizing action to the actors.

Deployment: The final step was the integration of the developed submodels into an overarching IT-solution. This included linking the individual prediction models to a prediction of customer orders across the entire SC (door-to-port ETA) as well as connecting this model to the expert-system. In addition, measures for the implementation of a future productive system were elaborated. In addition to a definition of data and interface requirements, a web-based prototype with a graphical user interface (GUI) for the visualization and interactive testing of the created solutions was developed.

The data activities as well as the development of the submodels and prototype were largely performed with R and SQL.

4 Results

4.1 Requirements and process analysis

During the analysis, several distinctions between the involved processes of the considered SC were identified, which have an influence on the development. This included the temporal determinacy of the processes by plan data, the causes for delays, the data availability, and the required reference points and objects for the ETA. Due to these differences, it was recognized that it is not useful to develop an overarching prediction model for the entire SC. Instead, the chain from the shipper to the seaport was divided into five subprocesses (see Figure 3). For each of them, at least one process-specific submodel has to be developed. Therefore, three representative pilot relations were defined: starting from the inland terminals Leipzig-Wahren, Munich-Riem and

Regensburg-Ost with their roadside pre-carriage transports via the MY in Maschen to the four container terminals in the seaport of Hamburg.

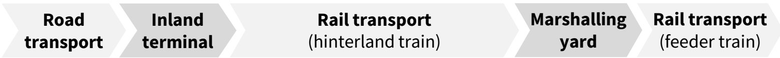

Figure 3: Considered subprocesses for the model development

4.2 Data analysis

4.2.1 Data acquisition

In total, during the project historical data for four years (2015 to 2018) from 16 different IT-systems of the participating companies was acquired. For the pilot relations, this included process data of 50,000 rail transports, 96,000 road transports, and 8.6 million container-related events. In addition, operational and external information on the individual processes was obtained, which depicts relevant influencing factors. This comprises personnel planning, vehicle characteristics, route and infrastructure information as well as construction sites, geo-data and weather conditions.

The highest data coverage was provided for rail transports. Firstly, detailed process data was available, since actual and planned times for the trains were recorded at discrete tracking points. Secondly, standardized disruption information for delays and many influencing factors were given. Usable data on marshalling processes in the terminals did not exist. For the road transport, actual departure and arrival times as well as start and destination points could be provided. In contrast to rail, no data was available on detailed routes, e.g. by GPS tracking. Also, disruptions were only recorded manually and not in a standardized way, so they were not considered. The data for the inland terminal and MY included the actual entry and exit times of the containers, wagons and trains. From this, i.a. the cumulative utilization could be determined. For the MY, planned times as well as information on the planned connecting trains of each container, respectively wagon were also available.

4.2.2 Data preparation

Due to the large number of involved IT-systems, merging them as well as ensuring a consistent database represented a major challenge. It was found that complete data coverage was not available for all customer orders, as some systems were only introduced at a later point in time (on certain routes) or data for older periods was deleted as part of the companies' data housekeeping. In addition to the completeness, a quality analysis was performed to identify anomalies. In particular, the extremes were considered, as these often indicate incorrectly recorded data. In addition, logical relations between the data were also reviewed, such as the fact that the departure must occur before the arrival. In many cases, implausibilities are due to manual data entry, e.g. the arrival time of trucks at inland terminals. Several measures were taken to ensure that all data sets could be used, despite the limitations in availability and quality. This included a transformation of syntactically incorrect data, a completion of missing values by predicting the most likely value based on other cases, and a selection of ML methods, which are explicitly suited for learning from incomplete training data sets.

4.2.3 Data analysis

After processing the data, various analyses were created to derive more operational information. By integrating the actor-specific systems, it was possible for the first time to derive statements about the total lead time of the containers along the SC, including actual times, planned times and delays, as well as about time-shares of the subprocesses. Figure 4 shows the distribution of the container-related total lead time for one of the considered relations from shipper to seaport for the years 2015 to 2017. For this relation, the median time is approx. 56 h. It shows a high variance with a strongly left-skewed distribution, which underlines the susceptibility to disruptions. In part, the long process times are also due to longer planned dwell and buffer times in the logistics nodes.

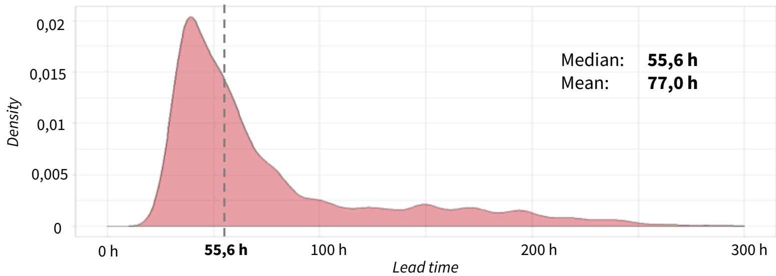

Figure 4: Distribution of total lead time

Figure 5 shows the lead time of this relation broken down into the individual subprocesses according to their time-share for the years 2015 to 2017 (arithmetic mean). A high proportion of around 70% is accounted by the logistics nodes. A major reason for this is the prevailing conservative planning of the SC, in which uncertainty about possible disruptions is to be compensated by additional planned dwell times in the nodes. The deliberate reduction of risk buffers through increased transparency represents a high potential for the ETA prediction. Rail transport between the inland terminal and MY takes up a share of about 20% of the total time. In contrast, road and rail transport between the MY and the seaport show low time-shares. Finally, it should be noted that the use of the arithmetic mean as an estimator for the average process duration and the existing skewness of the temporal distributions overestimate the dwell time in the nodes.

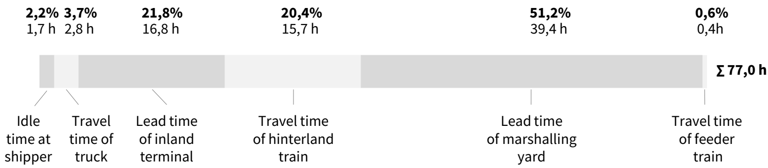

Figure 5: Lead time of subprocesses (absolute and ratio)

4.3 Model development

4.3.1 Prediction

To realize the ETA prediction for the SC, six process-specific prediction problems were derived, for which separate submodels were developed. In the first step, the travel time for the road delivery of the container between the shipper and the inland terminal is predicted. In the next step, a prediction of the achievable connecting train in the inland terminal is executed, considering the operating conditions. Afterwards, the arrival time of the train between the inland terminal and the MY is estimated, implicitly including the marshalling processes in the terminal. For the MY, the achievable connecting train to the corresponding destination terminal in the seaport is then determined. Finally, the rail transport to the port is predicted. The two sections of the rail transport in turn consist of further submodels for predicting the departure delay as well as the travel and stop times on the route, whereas each individual section between two tracking points or stations on the route is predicted individually. The overall prediction (door-to-port ETA) is composed of a logical connection of all individual submodels in the sense of a process chain prediction, in which the models successively build on each other: the output of a model serves as the basis for the subsequent partial prediction. As part of the iterative procedure for developing the submodels, the model configuration shown in Figure 6 was identified as the most suitable solution approach.

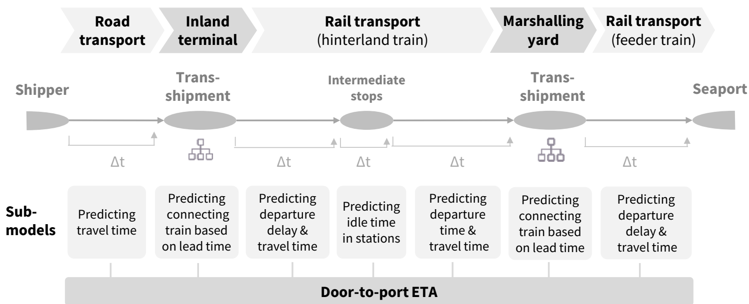

Figure 6: Process chain prediction approach for door-to-port ETA

During the model development, process-specific features were identified for each submodel and evaluated in terms of their importance as part of a feature selection process. A total of approx. 50 relevant features were identified for the submodels. Table 1 shows a sample of the considered features types, which map important operational influencing factors and disruptive events.

Table 1: Types of considered features (sample)

Feature type	Feature (generalized)
Infrastructure	Route information, construction sites, utilization, historical process times
Technical resources (especially vehicles)	Fleet planning, availability, vehicle characteristics, loading condition
Human resources	Shift planning
Freight information	Type, size, weight
Weather	Wind, precipitation, temperature
Time	Vacation, hour, weekday

The importance of two exemplary features for the subprocess of rail transport on one relation is shown by their correlation with travel time in Figure 7. A positive correlation is observed for the size of the train mass. Higher mass are associated with longer total train travel times. One of the causal reasons for this is the slower acceleration and braking behavior of trains with a high total mass. Furthermore, correlations were also found for the traction unit type. Causal reasons for this are different vehicle characteristics of each type, such as traction power and maximum running and braking speeds.

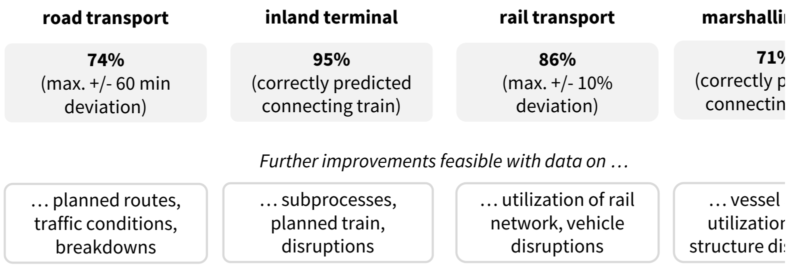

Figure 7: Correlation of train characteristics and travel time

Under consideration of the input variables according to the respective features and the target variables, the model configuration was performed. The output determined the type of prediction problem in the form of a regression or classification (Russell and Norvig, 2010). Transport processes were modeled as regressions since the output is a continuous variable. Classifications were used to predict the connecting transport at the inland terminal and MY. To identify the respective prediction algorithm, different ML methods were tested for each model. Overall, a combination of random forest, gradient boosting and linear regression trees was the most suitable approach. The suitability of the chosen ensemble learning methods can be explained by their specific properties. They can be trained well, even in the case of a high number of features (especially in terms of many binary variables due to a prior hot encoding of categorical variables) and small data sets. Another advantage is the automatic feature selection. Furthermore, these methods are well suited for learning from noise and incomplete data as well as they do not require extensive data preparation (Kuhn and Johnson, 2016).

By tuning the models, it was finally possible to achieve the prediction results shown in Figure 8 for the individual subprocesses of the SC. In this overview, the quality is measured on the basis of specific intervals, which the respective process participants have declared to be reasonable from an operational point of view. The prediction is always made before the respective process has executed, e.g. before a train departs. For the road process, 74% of the transports are predicted within a deviation interval of +/-60 min in relation to the actual time. In the inland terminal, the correct connecting train is predicted in 95% of the cases. For rail transports, the arrival time of 86% of the trains is correctly predicted within a +/-10% deviation interval. A correct prediction of the connecting train in the MY is performed in 71% of the cases, with a no-information rate of 37%. Overall, the individual processes can be predicted with a high to very high accuracy by the selected model approaches. Following the composition of the individual submodels, very good results could also be achieved for the overall prediction of the considered SC (door-to-port ETA). According to this, the prediction deviations from the actual times for the transports from the shipper to the seaports, which often take several days, amount to a two-digit minute range for many orders.

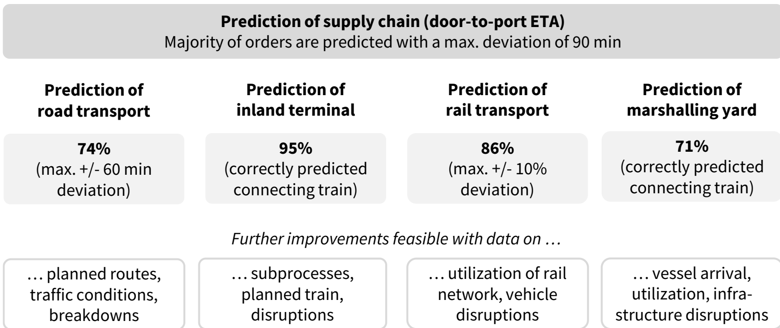

Figure 8: Prediction results and improvement potential

In the course of development, various levers for improving the prediction models were identified, which are also outlined in Figure 8. In general, high amount of training data and a coverage of relevant influencing factors by appropriate data are essential success factors. These requirements differ considerably in the individual processes. This explains, e.g. the better results for rail compared to road transport, where important information was missing like planned routes, breakdowns and stopovers. In the case of the inland terminal, this comprises data on the planned time of loading in order to consider planned storage times of the containers in the terminal. At the same time, data differences for the submodels with respect to the individual relations also become apparent. In the case of rail transport, the highest prediction quality was achieved on the relation with the best data coverage, which has an average travel time of approx. 15 h (see Figure 9).

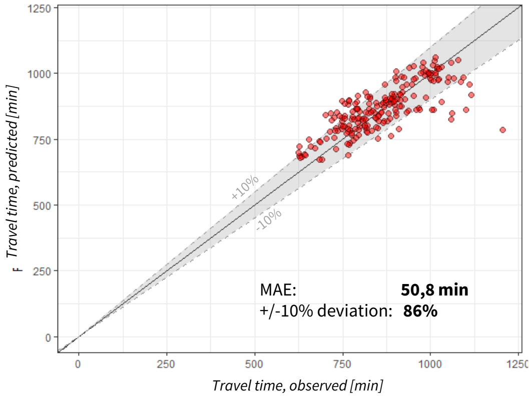

Figure 9: Prediction results of train transport

Across all processes, it can be stated that some influencing factors, such as technical disruptions to the infrastructure and to the used vehicle, as well as traffic-related influences and extraordinary disposition decisions, could not in principle be sufficiently considered in the prediction models on the basis of the available data. This also applies to large one-off disruptions that occur infrequently but have a high temporal impact, such as storms or strikes. Due to the pronounced individual character and the small amount of data available on these influences, the used ML algorithms cannot derive meaningful approximating relationships for the reliable prediction of new cases.

4.3.2 Prediction-based measures

Various use-cases for an ETA prediction were identified in the application area. These ranged from actor-specific optimization options, e.g. for shift planning in the logistics nodes, to timely synchronization of the entire SC. Latter option was linked with the highest potential for the envisaged solution, since reaching planned connection processes on time is of great importance in multimodal SC. In case of delays, even at the beginning of the transport, this can lead to high conflicts with downstream processes. Especially, missing an ocean vessel at the seaport can induce delays at the destination lasting several days or even weeks. Based on missing the corresponding vessel closing, various operational situations (conflict cases) in the SC were identified that can lead to this scenario and that can simultaneously be detected in advance by the realized prediction. For that, suitable actor-specific measures were collected and evaluated with regard to their potentials, effects and feasibility. Some of them are listed in Table 2.

Table 2: Measures for preventing closing exceedance at the seaport (sample)

Actor	Measure
Freight forwarder	Register late-arrival at the seaport
CT operator	Transfer to earlier train from inland terminal
CT operator	Transfer to entire road transport to seaport
Inland terminal	Prioritized train disposition in inland terminal
Railway undertaking	Prioritized wagon disposition in MY
Railway undertaking	Prioritized train disposition in MY
Railway undertaking	Prioritized wagon disposition in seaport

The identified conflict cases and measures were transferred to an expert-system, whose general operating principle is shown in Figure 10. It starts with the generation of an order-specific transport plan for the entire SC, which contains planning information on processes, times, locations and resources. In addition, the door-to-port ETA prediction is executed. On this basis, a comparison is made between the plan and the prediction. In the case of a detected deviation, its impact is evaluated. Once there no negative impact on the achievement of the vessel closing of a container, but it exceeds a defined threshold, a warning message is generated. Once the closing is exceeded, an automatic selection of suitable measures is triggered. The corresponding evaluation is based on logical decision rules. Firstly, this prioritizes measures that are most likely to prevent a missing closing. Secondly, measures that are associated with a high dispositive or financial effort are only proposed if alternative measures cannot be executed.

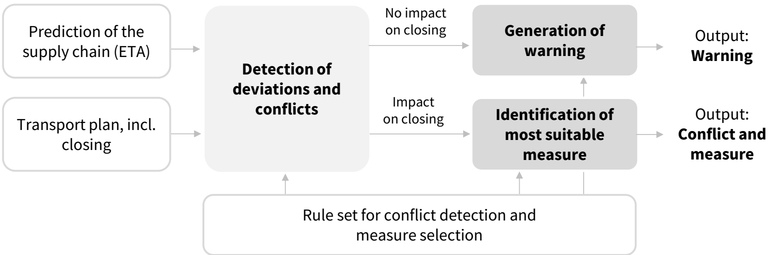

Figure 10: Operating principle of the expert-system

4.4 Deployment

The developed prediction models and the expert-system were transferred into an overarching prototypical IT-system (see Figure 11). This self-learning system consists of various subcomponents. It includes a module for training all submodels on the basis of the historical data from the 16 IT-systems, which also allows to check the quality and to retrain the model with new data. Another module applies the prediction results to new customer orders, detects deviations from the planned process sequence and performs the generation of measures. A web-based GUI was implemented for the prototype, allowing the retrieval of selected and anonymized orders. The system is publicly available on the website https://www.smecs-eta.de.

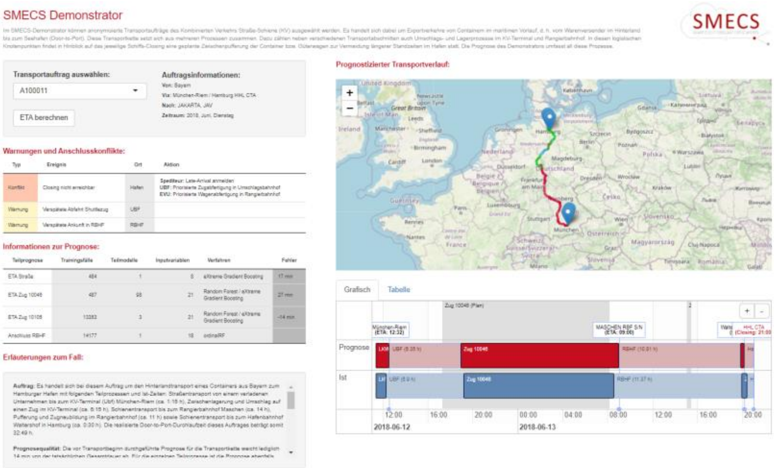

Figure 11: Web-based GUI of the prototypical IT-system

5 Potentials and limitations

By the developed self-learning decision support system, a contribution is made to the increasing need of transparency in logistics by providing reliable information on the arrival times of customer orders at important points along the SC, together with actor-specific recommendations for action. This information is already available at the beginning of the processes and considers effects on the entire SC. This enables companies to proactively select suitable decisions in the predicted event of a disruption, like a conscious prioritization of orders or an adjustment of capacities to achieve a higher adherence to schedules. At the same time, the efficiency and sustainability of processes can be improved by avoiding lower utilization and idle times of transports as well as cost-intensive exception processes, such as air or courier transports. This also includes the fact that deliberately planned risk buffers can be reduced, e.g. inventories in overseas plants or buffer times in logistics nods. Instead, the actual demand for required infrastructure, resources and transport capacity can be determined, which positively influencing the utilization and thus the ecological footprint of processes. At the same time, the improvement in the decision-making basis reduces manual and time-consuming planning and coordination efforts for involved actors. With the help of these positive effects (see Figure 12), the obstacles of shippers and forwarders to use multimodal SC are counteracted by ensuring efficiency, flexibility and reliability comparable to other modes of transport.

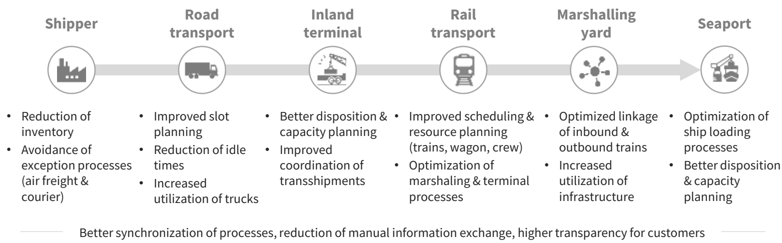

Figure 12: Potentials of the self-learning system

A main limitation of the research is the technical maturity of the developed IT-system. The prototype demonstrates the functionality for selected historical orders, but is not a productive system. The evaluation of the models was carried out under laboratory conditions using only historical data. Thus, no statements regarding the performance of the approach under real conditions can be provided. In future research, the system should be investigated under these conditions in the context of a field test. In addition to the prediction quality, other properties such as usability and acceptance must be evaluated in this context. Furthermore, the investigation has only been carried out for a specific process chain in terms of the maritime pre-carriage in combined transport on selected relations. A validation of the developed models on other transport modes and relations, including the transfer to the entire maritime SC, should be a subject of future research. Some important influencing factors are not considered in the solution due to the lack of data. In particular, the consequences of infrequent disruptions, which nevertheless have a high impact on the processes, could therefore not be predicted. Future research should examine how such disruptions can also be included.

6 Summary and outlook

The paper demonstrates the feasibility of a ML-based approach for the calculation of reliable predictions of multimodal SC. For the first time, a door-to-port ETA is provided, which allows a proactive intervention in terms of disruptions. The approach of implementing different ML submodels for several processes shows the best prediction results due to process-specific data and operational requirements. During the development of the models, it became apparent that the quality varies both in the individual processes and on the various relations. The achievable quality is strongly related to the available data, which show large differences along the SC. There is a lower coverage in road transport and inland terminals compared to the rail transport. Important factors influencing the process times are identified. Especially infrastructure disruptions, propagation of delays in the network and limited staff availability have a high significance. Frequent disruptions are well considered by the prediction, whereas unusual events require other approaches due to lack of data availability. After testing several ML algorithms and model configurations, ensemble learning approaches based on decision-trees show the best results for the most of the problems, since they are suitable for many variables with a small amount of training cases.

To support corresponding decision-making based on the prediction, the knowledge of involved actors was formalized within an expert-system. The identified measures show that there are different actor-specific possibilities for preventing upcoming disruptions. The used symbolic AI approach enables an objectively selection of suitable measures for an optimized planning and control of the SC. For the interaction of the prediction models and the expert-system a prototypical IT-system with a GUI was developed. This solution accelerates further research and the deployment of a productive system, since it provides insights in the model development and demonstrates the potentials of ML for SCM based on real customer orders.

The results of the research project are continued by DB Cargo AG in an internal project in order to provide a dynamic ETA prediction for its own transports at shipment level by a live operating system in the future. The authors apply the findings to other SC configurations. Together with shipping companies and terminal operators, they are developing ML-based ETA predictions and corresponding optimization measures for national and international inland waterway freight transports within a further research project (IHATEC, 2020).

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