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Forecasting Reliability Of Shipping Times In Single Wagonload Networks

Timo Ramsdorf, Birgit Milius

TU Berlin, Berlin, Germany

Abstract

Due to e.g. technical difficulties, complicated processes and missing personnel, single wagonload freight is a complex transportation system. One major problem are long and unreliable shipping times as these are influenced by many different aspects. In this paper, a model is proposed that forecasts the reliability of shipment relations in a single wagon network. This can also improve the estimation of the effects of changes in the network structure. The model maps the essential processes of railway operations onto a graph structure. By validating different model variants, some aspects could be identified as less important and other aspects as major influencing factors for the forecast of reliability.

Keywords: forecast, rail, freight, reliability, single-wagonload

1. Introduction

This paper presents a forecasting model that can predict the long-term reliability of shipment relations in single wagonload transportation. On the one hand, this is a forecasting task that depends on many factors, and on the other hand, it is a very relevant problem for increasing the attractiveness of sustainable rail freight transport.

At the beginning of the paper, the introduction describes how the German DB Cargo's single wagonload network is organized. Some terms are defined that are important for the following structure of the forecast model. Chapter 2 defines different variants of a model with their input and output variables and the assumed basic interdependencies. The forecasting problem is solved analytically with an algorithm using a graph-theoretical representation of these interdependencies.

As it is not clear at this point whether the forecasted shipment times adequately reflect reality and thus whether the model assumptions made are tenable, the models are validated in the following Chapter 3. The validation is done on a subset of selected transport relations. Two validation approaches are used. In the correlated inspection approach, individual shipment times are determined for each shipment, whereby correlations are implicitly considered. This method is therefore suitable for making statements about the relevance of the assumed interdependencies. In the second validation approach, the models are applied with aggregated input variables, which makes it possible to assess the influence of correlations.

1.1. Motivation

In the context of climate change, it is desirable to use rail for as much freight transport as possible in order to reduce CO2 emissions. Due to the smallest possible consignment unit (one freight wagon), single wagonload transport is in particular competition with truck transport compared to other forms of rail freight transport (Stuhr et al., 2023). In order to achieve greater climate protection in transport, the German government is pursuing the goal of increasing the share of rail freight transport in the modal split to 25% by 2030 (BMDV, 2021). Reliable single wagonload services can therefore make a significant contribution to achieve this modal shift.

At the same time, however, shipment times in single wagonload transport are subject to comparatively large fluctuations. Due to the complexity of the system, even small deviations in available capacity or travel time of trains can have a major impact on shipment transit times. Good forecasting models for the distribution of shipment times can help to understand these relationships better. As a result, the reliability aspect can be considered more precisely in network and timetable planning, which ultimately also makes the shipment times that actually result during operation more stable.

1.2. The Single-Wagon-Load Network of DB Cargo

Single wagonload traffic is characterized in particular by the fact that there is a fixed network through which a wagon or a group of wagons can be transported from any connected freight transport station via several trains and shunting facilities to any other connected station (Stuhr et al., 2023). In this network, the vertices represent so-called marshalling yards, which are connected via edges on which one or more scheduled trains run.

DB Cargo AG is a subsidiary of Deutsche Bahn and operates the largest single wagon network in Germany. The data sets used for validation in this paper originate from this network. The marshalling yards in Germany are divided into three groups depending on their size and importance, giving the network a hierarchical structure. (Stuhr et al., 2023)

The basic framework for service and network planning is the timetable, consisting of a set of *timetable trains*. A *shipment* is considered to be a transport order from one *freight transport station* to another. A shipment can consist of one or more *wagons*. The transport of a shipment is realized by an alternating sequence of train runs and *changeovers* in the marshalling yards. The sequence of marshalling yards at which changeovers take place is called the *shipment route*.

A train can consist of several blocks of wagons. In analogy to the departure and arrival time of a train, a block has a *collection end*, up to which wagons can be added to the block in the departure marshalling yard, and a *resolution end*, up to which a block is broken up at the destination marshalling yard. In contrast to departure and arrival times, this planning layer includes in particular the times for train break-up, shunting operations and train formation in the marshalling yards.

The reliability examined in this paper always refers to the long-term view of one fixed shipment route. In this case, long-term means that no statement is to be made about the arrival of a single shipment in a real-time situation and on a specific calendar day, but rather that a long-term distribution of shipment times can be specified.

1.3. Related Work

In (Marinov et al., 2012) it is outlined that rail operations planning is an active area of research and many decision support models have already been developed in collaboration between research and the rail industry. However, it is also emphasized that there is a need to adapt these models and goals to changing requirements of transport customers, such as smaller volumes and higher reliability.

For example, with the aim of avoiding capacity-related congestion in the single wagonload network, a mathematical optimization model was developed in (Krauth and Haalboom, 2022) to increase the understanding of the effects of rerouting and thus improve short-term rerouting decisions. In (Bruckmann et al., 2014), a model was developed to enable more efficient network planning. For this purpose, the agent-based mobility simulation MATSim (cf. Horni et al., 2016) was adapted to the operation of single wagonload traffic. One major change that has been implemented in European single wagonload transport is the XRAIL network, in which several railroad companies have joined forces. In addition to improved interoperability, this enhanced capacity planning also has a positive impact on transparency and reliability for customers (Schäfer and Rabet, 2012). The trains to be used for a shipment are booked in advance, which means that the marshalling yards no longer primarily work according to the FIFO principle (Stuhr et al., 2023).

In (Minbashi et al., 2021), a method was developed to classify the trains at a large marshalling yard according to the delay or earliness of their departure time. Decision trees and random forests were trained accordingly, so that a forecast is possible that increases the reliability of single wagonload traffic. In (Preis et al., 2018) the focus is also on the marshalling yards by applying an optimization model to the internal processes with the aim of improving the efficiency of the entire single wagonload network

However, among all these models, the forecast of the reliability of long-term shipment times considering the entire processes in a single wagonload network is still a gap that shall be addressed in this paper.

2. The Proposed Forecasting Model

To be able to make a forecast of the shipment time, the reality of the transportation system is represented in an abstracted, simplified model. The model definition in this chapter indicates what these abstractions consist of and which input and output variables the forecast model has. A graph structure is then created that builds on and represents the essential relationships of the model. Finally, the forecasted distribution of shipment transit times can be determined on the basis of this graph.

2.1. Model Definition

The timetable of all trains in the single wagonload network is taken as a fixed external condition. However, days of service are only specified on a weekday basis and not in relation to a specific calendar day. A representative week is taken as the timetable, i.e. special trains or timetable changes due to public holidays are not considered.

The forecast also always refers to a specific shipment route, which is defined by a start, a destination and an ordered sequence of changeover locations in between. The model basically assumes that a shipment cannot use a connection that has a different sequence of changeovers, which also rarely occurs in reality. This does not refer to the route of the trains in the geographical track network, but to the train connections between changeover points. It is also assumed for simplicity's sake that there are no trains with direct connections with which a wagon could skip a changeover in the route.

Other constraints that must be met are the capacity limits of the trains. For physical reasons, each train has a maximum length and a maximum mass, neither of which may be exceeded.

The model is based on the hypothesis that the shipment time in the real single wagonload network is significantly influenced by the following three interdependencies. If the next departing train at a changeover point does not have enough free capacity in terms of mass or length, the shipment cannot be allocated to this train and must remain at the changeover point until the next train in this direction is scheduled. The second aspect is train cancellations, which have the same effect. The third relevant interdependency is that a planned changeover does not work due to arrival delays or early departures because the changeover time gets too short. In reality, a planned changeover might not work even with punctual trains due to internal processes in the marshalling yard. However, this and similar factors are not considered in this model because many input variables would be necessary for which there is insufficient data.

Let the number of changeovers of the considered shipment route be n. The timetable defines a set of trains on each connecting section between two changeover points as a fixed framework condition. These sets are called $Z_0, \dots, Z_i, \dots, Z_n$ where i is the index of the changeover points of departure. The set of all trains is $Z = \cup_{i=0}^{n} Z_i$.

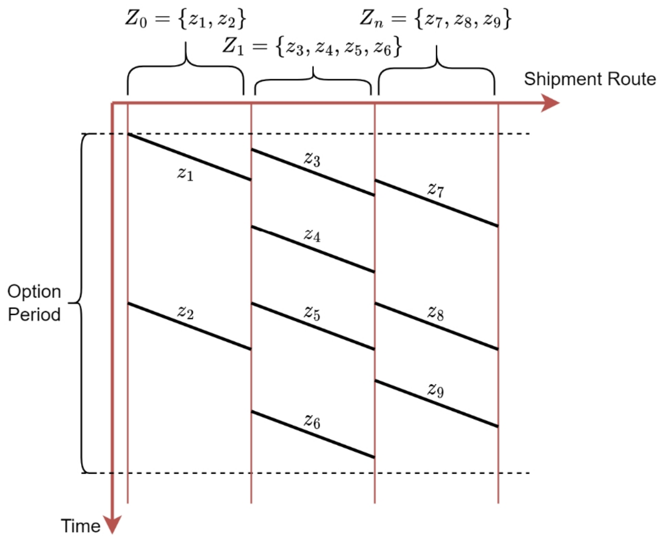

Fig. 1. Example of a schematic timetable for a shipment route with two changeovers.

The interdependencies assumed above, which are to be represented by the model, result in various necessary input variables that exist for each timetable train in the model ($z \in Z$): For the necessity of sufficient free train capacity, there are two stochastic distributions for the unallocated length and unallocated mass of a train as input variables. In combination with the parameters for the length and mass of the wagons to be transported, a random variable C_z can be derived from this, which indicates the remaining capacity of the timetable train z in number of wagons. The aspect of train cancellations is modeled with a percentage traffic day quota q_z and can be seen as a Bernoulli distributed random variable. For the interdependency of the changeover times, a train journey also has random variables for the departure (D_z) and for the arrival (A_z), which each indicate the distribution of the real times including the delays. In general, the distributions for delays and capacity are to be understood as conditional random variables under the condition that a train is not canceled.

All these distributions are read and aggregated from the historical recorded data of DB Cargo and are therefore discrete. The aggregation is done per timetable train and per day of the week. It is assumed that all random variables of a timetable train and between different timetable trains are stochastically independent to each other. Even if the observation period is longer than one week, so that timetable trains occur several times in the model on the same day of the week, their weights are considered to be identical but independently distributed. In reality, it is likely that this assumption does not apply completely. How strong correlations are in reality and how realistic this assumption is will be investigated in the validation study.

The forecast result returned by the model is the stochastic distribution of the shipment time, i.e. the difference between arrival time of the shipment at its destination freight transport station and the departure time at its origin freight transport station.

2.2. Mapping the Model onto a Graph Structure

The transportation options are represented by a directed and weighted graph, because then the question of how many wagons can be transported through the network in total can be represented as a maximum flow problem and solved accordingly.

The nodes and edges of the graph vary depending on route and timetable. However, the graph structure always follows the same pattern. There are always two fixed nodes, s and t, which represent the shipment's origin and destination. The other nodes are arranged in columns between them: For each changeover location, there is a column with arrival nodes and another column with departure nodes. Between a departure node (or the start s) and an arrival node of the next changeover location in the shipment route (or the destination t), there are directed edges that represent the timetable trains. Between an arrival node and a departure node of the same changeover location, the edges represent possible shunting transitions between the trains. Due to possible delays or early arrivals, all changes (both planned and those not possible according to the plan) are stochastically functional with a certain probability. Therefore, corresponding edges are inserted into the graph for all conceivable changeovers.

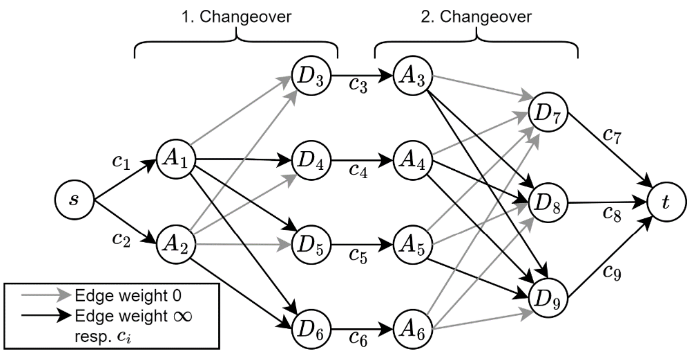

Fig. 2. The resulting graph structure in reference to the example in Fig. 1. The edge weights are simplified as a possible realization scenario of the actual random variables.

The graph is built up for a certain period of time, the so-called option period. This period begins at the time of the earliest possible departure of the shipment and ends at the latest possible arrival. When building the graph, exactly those trains are considered that depart and arrive in the option period.

The resulting graph G has the vertex set $\mathrm{V}(G) = \{\mathrm{s}, \mathrm{t}\} \cup \bigcup_{i=0}^{n-1}\{A_z | z \in Z_i\} \cup \bigcup_{i=1}^{n}\{D_z | z \in Z_i\}$.

The edge set *E(G)* is the union of the train edges

$$\{(s, A_z)|z \in Z_0)\} \cup \{(D_z, A_z)|z \in Z_1, \dots, Z_{n-1})\} \cup \{(D_z, t)|z \in Z_n)\}$$

and the changeover edges

$$\cup_{i=0}^{n-1}\{(A_x, D_y)|x \in Z_i, y \in Z_{i+1}\} .$$

The weighting of the edges indicates how many wagons can use them. However, since all input variables are stochastically distributed random variables, the edge weights are not fixed numbers either, but stochastically distributed variables.

For an edge that represents a ride of the timetable train z, the weighting is based on the input variable C_z, because this indicates how many wagons can additionally be assigned to this train. However, the edge weighting differs from C_z because here the probability of a train cancellation is additionally considered as a free remaining capacity of 0. For edges that represent a changeover, the weighting is always a Bernoulli distributed random variable that can be 0 or ***infinity***, depending on whether this transition is possible in time or not. The probability that a changeover works in time can be derived from the delay distributions of the arrival and departure events in combination with the minimum changeover time of the station, which are all given as model input.

This graph structure also represents the time component of the changeovers in the edge weighting. The problems of train capacities, train failures and changeover times have thus been abstracted to a common mathematical problem.

There are now two different ways of determining the possible number of wagons that can be transported in the option period from this graph. The maximum s-t flow indicates the number of wagons that can be transported if the wagons in the shipment can be split between different trains. If splitting is not possible, the s-t path with the highest total capacity can be determined instead. Both methods will be validated later as model variants.

However, the model should not only be able to determine the shipment capacity of an option period, but also return the distribution of possible arrival times for a given shipment quantity. This information can be determined in an iterative process in which the option period is repeatedly extended slightly. In each iteration, the graph is extended by the next timetable train. This is repeated until the probability that the transport capacity is at least as large as the given shipment quantity is sufficiently high according to the resulting distribution of the graph's transport capacity. The results of each iteration are accumulated into an overall distribution of arrival times.

2.3. Analytical Solution and Implementation

Many algorithms already exist for determining the maximum flow in a weighted graph. A well-known algorithm is that of Ford and Fulkerson. (Diestel, 2017). However, like most algorithms for determining the maximum flow, the Ford-Fulkerson algorithm works with graphs whose edges are weighted with natural numbers. In this case, however, the edges are weighted with random variables, i.e. it is a so-called random network. There are already algorithms for this case too, but they are very complex, e.g. the algorithm by (Frank and Hakimi, 1965). The complexity can be reduced by determining only estimates of the maximum flow instead of the exact result (Carey and Hendrickson, 1984). Since there is no productive application for this work so far and the calculations were mainly required for experimental validation, the maximum flow was calculated using a very trivial algorithm, which requires more computing time but is easier to implement. The individual permutations of the random variable values can be considered to cover all situations, because the random variables are all discrete. For a single permutation, a standard algorithm was then applied to determine the maximum flow with natural numbers as weights. The results of the permutations were then aggregated back into one weighted distribution.

The previous approaches have shown the disadvantage that it is very complex to calculate a stochastic maximum flow for general random networks. As an alternative, the following approach is based on the model variant without possible splitting of the wagon group of a shipment. In analogy to graph theory, this means that we are no longer looking for a maximum flow, but only for a path whose edges all have sufficient capacity, which can be solved with significantly less complexity. The proposed algorithm also benefits from the layered structure of the graph.

The algorithm considers consecutive cuts in the graph one after the other in the order of the shipment route. The cuts result automatically from the defined graph structure due to the set of edges for train rides on a shipment route section. A probability distribution is determined for each of these cuts, which indicates which train is used on this shipment route section and with what probability. The distribution of the first cut can be initialized deterministically by the given departure train. The distribution for the respective next section is then derived iteratively in two phases: First, the distribution of arrival times is calculated from the distribution of arriving trains. Then, depending on this, the distribution of the next connecting trains is determined. The probability that a connecting train will be selected depends on the probabilities of the changeover times, sufficient capacity, the cancellation rate and the condition that no previous train was selected.

For the further validation of the model, the algorithms described above were implemented in different model variants in Java17 using the framework JGraphT (Michail et al., 2020). As described in the model definition, the implementation takes the timetable data and distributions for delays, train capacity utilization and train cancellations as input. The historically recorded data from the DB Cargo AG data warehouse for almost every train ride in 2022 was available for this purpose. The data records were prepared according to the aggregation described above. For each specific shipment relation for which a forecast should be calculated, the route and the scheduled trains must also be defined by a fixed configuration.

In the validation, several model variants are to be compared, which differ, for example, in the possible shipment separation but also in other options. To ensure that the different model variants can be used with as little adaptation effort as possible, an abstraction pattern was developed in the implementation that can be used to call up all model variants in a standardized way. This means that the model can be automatically applied to a forecasting task and returns a forecasted distribution of shipment transit times.

3. Model Validation

The validation chapter first describes the structure of the validation study. The results of the various validation approaches are then shown.

3.1. Validation Methodology

Validation is carried out in two phases in order to distinguish between different potential sources of error.

The first phase is a validation according to the correlated inspection approach (Law, 2014). Each shipment that was transported in the historical comparison period is considered individually. It is important to note that the statistical distributions are not used as input data for the model, as is usually the case. Instead, specific values from the train rides of the calendar days are used. This has the effect that correlations between the model's input variables that might occur in reality are already taken into account. Errors arising from the assumption of stochastic independence of the model's input variables are therefore excluded from this validation phase. Instead, the results of the correlated inspection approach provide information on whether the assumed central interdependencies of the model can describe the reality or whether significant relationships exist in reality that are not considered in the model (Law, 2014).

In the correlated inspection approach, four different metrics are used for evaluation. For each metric, the shipments are counted for which the predicted and the historically actual shipment time fall within the corresponding acceptance period of the metric. In relation to the total number of shipments, a proportion can thus be determined that indicates the forecast quality of a model variant with regard to a shipment relation.

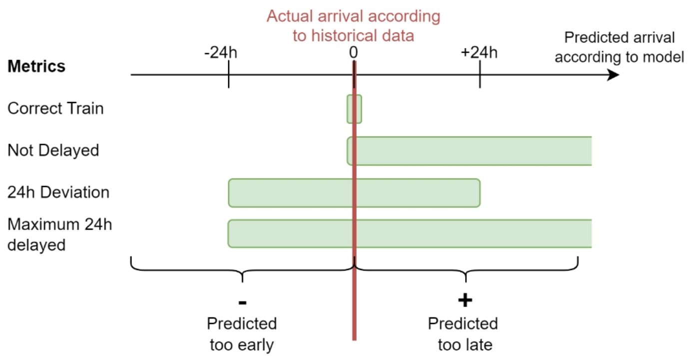

Fig. 3. The different metrics of the correlated inspection approach. The green bars show the acceptance period of a metric in which a prediction is considered as successful.

The strictest metric only accepts forecasts that hit exactly the right arrival train, so that it provides information about the accuracy of the model itself. In contrast, the metric “not delayed”, which tolerates an earlier arrival than predicted, would be relevant for the question of arrival guarantees to customers. For both metrics, there is another metric that has a 24-hour tolerance range, so that a gradation of the forecast accuracy is possible.

In a further step of the correlated inspection approach, the model results are no longer related to the individual trains, but a distribution of the transport running times is created. This is then compared with the real distribution of transport times from the historical data. The comparison is made both visually with regard to a similar shape of the histogram and by hypothesis testing, specifically using the Kolmogorov-Smirnov test.

The Kolmogorov-Smirnov test was selected here because it is suitable for comparing two samples with each other with regard to a common population without assuming certain properties such as a normal distribution. The null hypothesis that the test attempts to reject is that there is such a common population of both samples. With trend, dispersion, skewness and excess, this test can detect differences in the distribution function of all types (Sachs and Hedderich, 2006). The maximum distance between the distribution functions of both samples at any point is used as the test measure. The larger the test measure, the more different the two samples are and the more likely the null hypothesis is to be rejected.

The second higher-level validation phase, which follows the correlated inspection approach, is the aggregated validation. Here, model results are generated as in the normal application with aggregated distributions of input data. The resulting shipment times are grouped into blocks of six hours and a probability is assigned to each of these blocks. In particular, this means that correlations between the input data are no longer implicitly considered and the original assumption of statistical independence between all input variables of the model becomes effective. The comparison with the correlated inspection approach can therefore be used to estimate how strong the influence of correlations is. The real historical shipment times are also divided into blocks of six hours. This allows to assess the results of the model in the histogram and compare them with reality.

The validation methods encounter a problem in relation to capacity constraints. The forecast models estimate the shipment time for an ***additional*** wagon quantity, but the capacity consumption of the shipment to be validated is already included in the historical train data. A direct comparison of historical shipment times with forecast results would therefore tend to overestimate the shipment time. To counter this validation error, the capacity consumptions of the shipments under investigation are subtracted from the historical train utilization before the validation. In aggregated validation, several shipments can be defined as historical capacity consumptions, while in the correlated inspection approach, only the one shipment under investigation is subtracted.

As the model variants can only ever be used for a fixed relation, the validation must be carried out on a set of relations selected to be as representative as possible. In this work, eight relations were selected on which a large number of wagons and shipments were transported over the entire observed year so that the statistics are meaningful. It is also important that the routes are evenly distributed spatially. The selection was made in such a way that almost all marshalling yards at the highest hierarchical level in the German single wagonload network are covered by the selected sample. Elementary distinguishing features of the shipment route, which are also representatively covered by the selection, are the number of changeovers and the sequence of changeovers at the various hierarchical levels of the changeover points in the transportation network. The results of the following validation are either given for one of these eight relations or refer to the average of all these relations.

3.2. Results of the Correlated Inspection Approach

As shown in table 1, the results are very different for the various relations. There are relations on which the model generally provides very good results. The “not delayed” metric also provides reliable results with 94% with regard to potential customer guarantees for shipment times. On some other relations, however, the results are less accurate. On the worst relation, the correct arrival train was predicted in only 36% of shipments. Although the 24-hour metric is also not good compared to other relations, it has a significantly smaller difference than the metric of correct trains. There are many train connections on the last spatial edge of the shipment route. This indicates that the frequency of connections on the last spatial edge has a large influence on the metric of correct arrival trains. The otherwise occurring effect that the error tolerance for the last changeover increases when many time points are aggregated to one arrival train is then absent.

Furthermore, by comparing the model variants with and without capacity rules, the influence of train congestion on predicted shipment times can be determined. On some relations, the capacity restriction has little impact, while on others the forecast accuracy could be increased from 50% to 83% by taking capacity into account.

Table 1. Results of 4 metrics of the correlated inspection approach.

Transport Relation	Model Variant	Correct Train	Not Delayed	24h Deviation	Maximum 24h delayed
Best Relation	Fastest Connection	75%	78%	95%	97%
	Capacity Constraint	79%	94%	91%	99%
Average of all Relations	Fastest Connection	52%	61%	71%	77%
	Capacity Constraint	66%	83%	80%	90%
Worst Relation	Fastest Connection	12%	19%	62%	63%
	Capacity Constraint	36%	52%	69%	78%

There is one further relation where the forecast quality must generally be classified as worse than on most relations. When looking at the chronological output, however, an interesting temporal distribution of the forecast errors becomes apparent. Table 2 shows this by recording separate values for the periods up to March 31, 2022 and from April 1, 2022. It is clear that with 84% correct arrival trains in the period between January and March, the real transport times can be described very well by the model. In the following period, however, the forecast quality becomes much worse. This indicates that the general operating status of the transport network also has an influence on the shipment times of individual relations.

Table 2. Detailed results on one selected transport relation. In all cases the capacity constraint was applied.

Model Variant	Validation Period	Correct Train	Not Delayed	24h Deviation	Maximum 24h delayed
Changeover by constant minimum time	Total validation period	59%	66%	80%	85%
	Jan – Mar 22	84%	90%	92%	98%
	Apr – Dec 22	44%	51%	72%	77%
Changeover by collection and resolution end	Total validation period	57%	72%	81%	89%

The differences between the various model variants are examined in more detail in the following. For instance, there is the model variant that does not use a fixed minimum changeover time as before, but times for resolution and collection ends which can be different for individual train blocks. The influence of this additional factor is mostly positive, but not large. The proportion of correctly predicted trains with capacity has actually decreased. A detailed examination of interim results has shown that in many cases the cause of this is a changeover for which a shunting time is scheduled that is significantly longer than the minimum changeover time. Delayed incoming trains would therefore theoretically have meant that the planned connections were reached less frequently. In practice, however, these changeovers have often worked, although the remaining changeover time after delays is less than the time required according to the resolution and collection ends. This also explains the greater positive change in the "not delayed" metric. This leads to the suspicion that delays cannot be transferred linearly to a shift in shunting processes. Dispositive interventions in the shunting processes could probably be the reason for this.

The in terms of implementation more complex but also more accurate model variant with a possible splitting of the wagons of a shipment was carried out for all relations in the correlated inspection approach. Consideration of the capacity itself plays a major role, as it enabled the proportion of correct arrival trains to be increased from 52% to 66% on average. However, the additional consideration of a possible splitting of the wagons of a shipment onto different trains led to only minimal changes, so that still 66% of the arrival trains are correct.

On the one hand, it is noticeable in the historical transport data that, overall, the wagons of a shipment are rarely split. This may explain the small differences. There are some shipments for which an earlier arrival could have been achieved by splitting the wagons. In practice, however, this often did not happen. It is possible that this is often decided against due to the increased coupling and shunting effort involved.

Table 3. Results of the Kolmogorov-Smirnov-Test depending on the alpha-parameter.

Alpha-Parameter	Number of Accepted Relations	Number of Rejected Relations
0,001	8	0
0,1	6	2
0,9	4	4
0,999	4	4

Finally, in the correlated inspection approach phase, the Kolmogorov-Smirnov test is used to check whether the model provides a distribution of shipment times that is very similar to the historical distribution. An error probability alpha must be selected for the Kolmogorov-Smirnov test. This indicates the probability of a type 1 error. If alpha is set very high, the probability of a type 2 error is lower.

Overall, it can be shown that two of the selected relations tend to reject a common population. For two other relations, the Kolmogorov-Smirnov test cannot make a clear statement. For four relations, however, the test clearly shows that the model can reproduce the real distribution of shipment times well.

3.3. Results of the Aggregated Validation

In the aggregated validation, the models are applied with stochastically distributed input variables. The forecasted distribution of shipment times is summarized in blocks of six hours. The first 72 hours of the resulting probability functions of two selected transport relations are shown here as an example. All elementary interrelationships are representative of these.

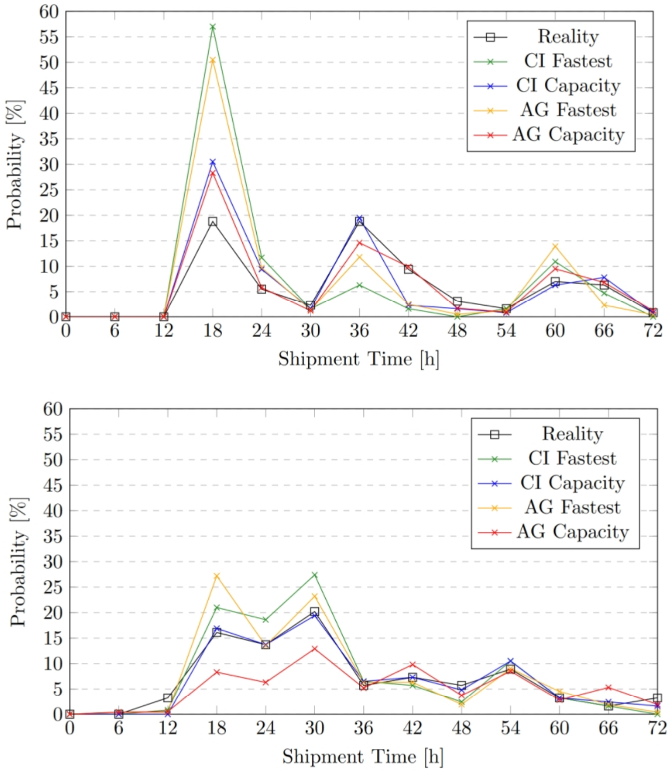

Fig. 4. The resulting probability functions of different model variants (Fastest Connection and with capacity constraints) applied to 2 example transport relations. The diagrams show the distribution of shipment times in reality, the aggregated predictions of the correlated inspection approach (CI) and the forecast of the aggregated validation (AG).

First of all, it should be noted that there are always some peaks in this type of histogram, which result from the timetable and the possible combinations of departure and arrival times derived from it. In addition, high probabilities are typically seen initially around the fastest possible connection. This is followed by smaller probabilities at intervals of one to two days for wagons left in gaps in the timetable around the weekend. These peaks can be reproduced in most places by all model variants, so that the basic shape of the probability function looks similar. The probability functions differ mainly in the varying intensity of these peaks.

In the upper example, it can be seen that the aspect of capacity dominates and that there are only minor differences between the correlated inspection distributions and the aggregated validation. The shipment times tend to be shifted to the right due to the capacity restriction and the probability functions clearly approach the reality, especially for the first two peaks. The respective comparison between an aggregated distribution in contrast to the corresponding correlated inspection distribution also shifts the transportation times to the right and thus comes closer to reality. Overall, however, correlations only have a small influence here.

The situation is different in the example below. Here, the correlated inspection distribution with capacity is very close to the distribution of reality in most places. In the distributions without capacity, there are no major differences between the correlated inspection curve and the aggregated curve except within the first three blocks. This indicates that there is little relevant correlation in the delay data. However, the probability distribution of the aggregated application of the model variant with capacity constraints looks very different and is obviously strongly influenced by correlations. There are probably strong correlations between the capacity utilization and delays or between the capacity utilizations itself.

4. Conclusion

In general, it should be noted that the validation results vary greatly. Both the overall model quality and the influence of individual factors such as capacity constraints and correlations differ greatly in some cases between the investigated transportation relations. This suggests that there are certain characteristics of relations and routes that strongly influence the quality of the models. However, no such connection can be established with regard to the number of changeovers and the hierarchy scheme of a relation. Instead, the long-term temporal fluctuations in forecast accuracy indicate that it is not the characteristics of a relation, but rather the operating situation or the condition of the transport system that have a decisive influence on the validation results.

The successful correlated inspection validation on some relations shows that the assumed interdependencies of the model are basically well chosen and can describe the real operational processes. However, there also appear to be other interdependencies that only occur at some locations and in certain periods of time and have a particular impact on the processes in the marshalling yards.

The result of the aggregated validation is that correlations do not have a major influence on every relation, but on most of them. Often only some individual input variables are affected. The assumption that all input variables of the model are stochastically independent should be revised in future. At least individual correlations should be considered in further developments of the model.

The comparison of the different model variants showed that the consideration of train delays and maximum capacities is very important. However, the use of resolution and collection ends and the enabling of wagon splitting resulted in no or only small improvements. Therefore, it is better to use a model variant without these aspects in order to obtain a model that is simpler and still has approximately the same explanatory power.

The resulting best possible model variant is therefore based on train delays, train cancellations, train capacity utilization and minimum changeover times for marshalling yards. These aspects are represented in a graph structure on which the path with the highest capacity is then determined. As the statistical comparisons with the Kolmogorov-Smirnov test show, the resulting distributions of shipment times based on these few but elementary interdependencies can reflect the real relationships of single wagonload traffic already very well.

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