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Application Of Machine Learning On Transport Spot Rate Prediction In The Recycling Industry

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Abstract

The transport spot rate in trucking logistics is an important factor for market participants in the recycling industry. Knowledge about the current spot rate is essential for operational decision-making in price negotiations between brokers and shippers. Due to the characteristics and dynamics of the industry, this task is particularly challenging. So far, businesses mainly rely on traditional calculation methods combined with their own expertise in price negotiations. The growing amount of existing business and market data may enable companies to take advantage of data-driven decision processes. However, the resulting volume of data and required effort for analysis do not match the fast pace of daily business.

To improve current forecasting practices, this paper conducts a comparative study of machine learning (ML) approaches for shipment-specific spot rate prediction. For this, the paper builds on the experience and database of a small broker in the recycling industry in Northern Germany and complements it with external market information. The study shows the ability of ML to internalize underlying patterns between spot rates and market data. During the use case the CRISP-DM framework is followed to select the most appropriate features and train multiple ML algorithms. Several metrics are applied to determine the most accurate model for spot rate prediction. Results indicate that especially the ML-algorithm Random Forest shows considerable potential to provide brokers in the recycling industry with more reliable spot rate assumptions. Therefore, future implementation of ML approaches in the industry may open up new and beneficial business opportunities. The study paths the way for further research on the predictive potential of ML for prices in transportation with extended and diversified data sets.

Keywords

Machine Learning; Price Prediction; Transport spot rate; Reverse Logistics; Recycling

1. Introduction

The latest supply shortages in Germany and Europe disclosed the urgency to exploit the possibilities of the circular economy for resource recovery to reduce dependency on primary resources [1]. The closing of material cycles by returning waste and product residues to reuse or recycle them is, together with narrowing and slowing the use of materials, at the core of this strategy [2]. Hence, recycling is an essential industry for closed loop supply chains. Along with the collection and storage, the transport of waste products is among the basic processes of logistics in recycling [3]. Since the management of logistics is rarely the core business of the waste owners, specialized companies handle the process. In recycling, a broker arranges the disposal of waste on behalf of others with or without taking possession of it [4]. To their customers they act as a disposer, whereas to carriers and disposal facilities they act as the waste producer. Thereby, they connect customers and disposal facilities providing efficient and economic transport of waste by contracting an appropriate carrier at the best costs [5]. For shipment, road transport via trucks is often the preferred solution due to their speed, flexibility and versatility [3,6]. Hence, brokers in recycling industry need to seek capacity on the trucking market.

In road transportation, freight rates are distinguished in contract rates and spot rates. Spot rates are a lot more volatile and at times exceed long-term contract rates by more than 60% [7]. Smarter algorithms and sharing economy have led to the rise of digital freight exchange platforms, giving the spot market even more importance [8]. In, addition, the recycling industry is characterized through extensive legal requirements shaping the competition [9]. Further certification and know-how are required to successfully participate in the market, which reflects on less elasticity of the available capacity. Moreover, less-than-truckload shipments are unusual and, depending on the type of waste product, additional permissions and cleaning processes of trucks are mandatory. These aspects enhance the existing uncertainty in price negotiations, as the rates for recycling and transportation of waste products underly high volatility [9]. Therefore, especially for brokers, who qualify through exquisite market knowledge and network, support in price prediction in such a dynamic environment is vital [10].

For spot rate predictions, experience and constant knowledge of market conditions are required. This is becoming a challenge for logisticians due to the ever-increasing amount of data in logistics and the special conditions of the recycling industry. Machine learning (ML) algorithms can be trained with large amounts of data and use this as input to determine a desired response value [11]. It has also been successfully applied to price prediction problems in various industries. The enhanced volatility of spot market prices in the recycling industry and specific infrastructural as well as geographical conditions in Germany amplify the demands on the forecasting model's capabilities. Thus, the study explores the ability of ML models to deal with these settings. The objective of this study is to provide a new prediction approach for market participants that comes with realistic rate suggestions on the spot. The subsequent section reviews the current state of research. Next, ML is applied in a use case based on business data. After identifying relevant features, several ML algorithms are applied to predict future spot rates. The last section summarizes the insights and conclusions for future research.

2. Theoretical background

ML has been applied to price prediction tasks in many research fields (e.g. housing [12], gas [13] and stock prices [14]). In the transport industry, the majority of studies focuses on sea transport (e.g. tanker [15], dry bulk [16] or container freight rates [17]). Studies on price prediction in road transport cover primarily estimation models for spot and contract rates using statistical approaches [18,19]. Some studies also use prediction approaches with ML. Xiao et al. [20] apply GARCH, NN-GARCH and ARIMA models to predict the volatility on the freight rate on the spot market. In another study, Xiao et al. [21] compare a lagged coefficient weighted matrix-based multiple linear regression model with ARIMA and light gradient boosting to predict short term spot rates in southwestern China.

Many studies predict the general price level over time. The forecasts are sometimes further specified to lanes or freight types imparting more specific information. With respect to brokers, simply observing price trends through an estimated index is often insufficient in daily operations. Market players value each transaction based on their individual network and know-how [22]. As every transaction is negotiated individually, spot rates for transport need to be considered shipment-specific. From the broker's perspective, the acceptance of neither the offer to the customer nor the bid to a possible carrier is certain at the time the quote is made to the customer [23]. Therefore, brokers face the challenge of pricing every single transaction with its characteristics in a profitable way to prevent economic risks.

Few researchers have addressed the problem of shipment-specific spot rate prediction. Kay and Warsing [22] develop a non-linear regression model to estimate freight rates for less-than-truckload loads in the US. The model considers various shipment characteristics and public data to provide decision support through shipment price prediction. However, no evaluation of precision of the predicted freight rates is conducted. In a study by Lindsey et al. [24] a data set of a non-asset based broker in the US was used to predict arising carrier costs for the broker. Determinants for carrier costs on spot markets were identified on lane- and shipment-level. In a tactical planning scenario, a regression model was applied to predict carrier costs on unprofitable lanes. The results showed a mean absolute percentage error (MAPE) of 27% on the respective lanes. In another study, Lindsey et al. [10] built a decision making framework for freight brokers on the spot market. The statistical modeling framework consists of decision and profit maximization models. When applied to real-world data, the framework provides a profitable price suggestion for a transaction with potential carriers. Budak et al. [23] applied an artificial neural network and quantile regression to make predictions for spot rates in Turkey in both a route-based and a general model. Route-based predictions emerged more precise than predicting single transactions in the general model. The artificial neural network provides more precise predictions for spot rates in the route-based model (MAPE 0.8 %), while quantile regression performed better in the general model (MAPE 6.7 %).

Few studies focus on analytical predictions on shipment-level and only one applies ML for this task. Therefore, this study aims to build on the shipment-specific studies by Lindsey et al. [24] and Budak et al. [23], by applying a set of ML algorithms for spot rate determination. In addition, the focus of this study on brokers in the recycling industry in Germany leads to special circumstances differing from the general approaches in the literature so far. No other studies covering this part of the circular economy were identified. Therefore, the present study demonstrates the applicability of ML for spot rate determination in the recycling industry by historical and current market data. It determines the best suited algorithms for the prediction task based on a set of evaluation metrics.

3. Methodology

This study follows the widely used Cross Industry Standard Process for Data Mining (CRISP-DM) developed by Chapman et al. [25]. The process contains six phases: “business understanding”, “data understanding”, “data preparation”, “modeling”, “evaluation” and “deployment”. In the business understanding phase, the underlying business objectives, current situation and goals for the project are assessed. During the data preparation phase the final data set used for modeling is built from the initial data. For this, tables and features are selected and additional external data is added. The data is then transformed to be processed during modeling. In the subsequent phase, modeling techniques are determined and applied for the task at hand. This step includes the iterative optimization of the data and model parameters. To determine the quality of the model and to ensure that it meets the expectations of the business, a comprehensive assessment of performance is conducted during the evaluation phase. In the last phase, the final model is deployed. This includes the integration of a closed application supporting or taking over the underlying process in the existing IT-system. The deployment phase is out of scope of this study. Data analysis and modeling is conducted in Jupyter Notebooks operating Python 3.1.0 and using libraries such as Numpy [26], Scikit-learn [27] as well as Pandas [28]. In the subsequent section this methodology will be applied to the use case.

4. Application on the use case

4.1 Business and data understanding

The data for this study is provided by a broker in the recycling industry in Northern Germany. The firm sources transport and recycling capacity for its clients and their waste products. As this study focusses on the road transportation of materials, the price for disposal is out of scope. Since the company is extensively using online freight exchange platforms for sourcing transport capacity, it is exposed to the dynamic rates on the spot market. The business intends to use its data to predict spot rates for future orders. The forecast shall support the order disposition process, where an employee needs to determine the value of an order within a horizon of 1 to 4 weeks based on past data.

The data set for this study consists of several tables containing order, customer, carrier, disposal facilities and product type information. These are merged to a main table consisting 14,244 transactions and 14 variables or features. The target variable in the data set is "freight rate". It is either stored as the total price or as price per ton. However, the spot rates in the transport industry are mainly negotiated as freight rates per km, which are not stored in the initial data set. The transformation of the target variable as well as data inconsistency issues and integration of features are addressed during data preparation.

4.2 Data preparation

The distance and duration for each transaction are obtained through an automated Google Maps API by passing the respective ZIP-codes and locations from the data set. Missing and incorrect data for the target variable are imputed or dropped, resulting in the final, normalized target variable "freight rate per km" (FR/km). The data set then contains categorical and numerical features reflecting temporal, geographical, cargo-specific information. Through an exploratory analysis the impact of features on FR/km is examined. Further data preprocessing steps such as cleaning, grouping, extracting or excluding features and transactions are performed [29]. For example, the lowest and highest 5% of FR/km are removed from the data set, as these rates do not represent the core business activities of the broker.

The numerical features, distance and duration both show a strong inverse correlation (ρ = -0.95), with the target variable. Transactions over short distances are significantly more expensive than long distance trips. Moreover, the time per km ('time/km') can be inferred as an additional feature. Slower trips, for example with longer sections on country roads or through congestion prone areas, show an increase in 'FR/km'. The weight of cargo revealed no interpretable relation to FR/km and was excluded. For categorical features, geographical features are used to group customers and disposal facilities into regions (North, South, East, West or old/new federal state). For trips between the respective regions, differences in FR/km are observed. Product waste types are further summarized into waste classes. As another feature, the carrier of an order is unknown at the point of prediction, unless the order is executed by a broker's truck. Hence, this high cardinality feature is split into two groups (broker, other). Other categorical features are derived from time-related features such as order and transaction date. Information such as day of week, month, quarter or seasons is extracted from them. FR/km shows variation over the course of the year due to differences in capacity availability. Concerning the weekdays, weekend transports are rare and expensive. On Thursdays, market players plan the trips for next week reducing the available capacity and pushing the freight rates. Integrating 'holiday' as an extra feature reveals an increase of FR/km in the days directly before the holiday, especially for short trips.

Some additional, publicly available external features with influence on FR/km are found. The diesel price per liter is available as a time-series data set on the web [30]. Moreover, the truck toll mileage index logs the truck volume on German highways [31]. From this, the available capacity can be inferred. When compared over time, both features accompany the current price level of FR/km and are consequently included in the model. The data preparation procedures result in a final dataset of 11,472 transactions and 23 features.

4.3 Modeling

The prediction task is a regression problem with a continuous target variable. After fitting the model to a training set, it will be tested against unseen data from the hold-out test set [29]. In the order disposition process a lot of past data is used to predict spot rates in a relatively short future horizon (1-4 weeks). However, for modeling, a test set with sufficient data and variety is required. Therefore, the training set is built with 90% or 10,324 transactions from the final data set (from 01.01.2015 to 22.04.2021). The test set consists of 10% or 1,148 transactions from 22.04.2021 to 24.08.2021. This procedure approximates the real application and is referred to as the 90/10 split. Results for the 90/10 split are not generalizable, however, as they could have occurred simply due to the selected composition of the training and test data sets [29]. For more reliable results, cross-validation is applied. In cross-validation the data set is divided into k-folds of alternating training and test subsets for each fold. The model is then evaluated by averaging the error of each fold to the overall prediction error [32]. Although the data set is not a time series in particular, the prediction task is time dependent since the goal is to predict exclusively future spot rates from the past. Consequently, conventional cross-validation cannot be used, since it would leak future information that will not be available in a real-world setting. Instead, time-based cross validation using 10 time-dependent folds is applied. By integrating a GridSearch algorithm the ideal parameters for each model are determined.

Before running the model, further preprocessing of numerical and categorical features is required. Numerical features are scaled using the StandardScaler algorithm. Categorical features are encoded using One-Hot Encoding. To reduce loss of performance caused by high dimensionality after encoding, a feature selection process is applied on the data set. Only the most relevant of the encoded features are passed on to the model as boolean features. Several feature selection methods have been compared to determine the number of features leading to the best performance. Out of all compared methods, SelectKBest for regression problems yielded the best results. It was found that performance peaks, when the 11 best features are used for modeling. The final features for the model are listed in Table 1.

Table 1: Final set of selected features for modeling

	Variable	Type	Importance	Meaning
1	curr_diesel_price	numeric	0.31	Current price for Diesel fuel at the time of order
2	distance	numeric	2.10	Distance covered during trip
	distance_cat:	categorical		
3	▪ dist_medium	boolean	0.32	Category, TRUE for trips 60 km to 150 km
4	▪ dist_long	boolean	0.35	Category, TRUE for trips > 150 km
5	truck_toll_index_adj	numeric	0.20	Current Truck Toll Index seasonally adjusted at the time of order
6	frforw_kat_1	boolean	0.18	Category, TRUE for transactions with freight forwarder 1
	direction_transport_old_new_state:	categorical		
7	▪ "new_new"	boolean	0.25	Category, TRUE for trips within new federal states
8	▪ "new_old"	boolean	0.22	Category, TRUE for trips between new and old federal states
	direction_transport_region:	categorical		
9	▪ „north_north"	boolean	0.19	Category, TRUE for trips within regions in Northern Germany
10	▪ „east_east	boolean	0.16	Category, TRUE for trips within regions in East of Germany
11	time_km_breaks	numeric	2.00	Time per km including mandatory breaks [sec]

After feature selection, the authors tested the predictive performance of several ML algorithms on the set of features. As a benchmark, a simple model (BM) is used. The BM reflects estimation principles applied in business so far. During training, the BM calculates individual average spot rates for short (<60km), regional (60-150km) and long (>150km) transports. Surcharges are added for trips directly before public holidays and orders closed on Thursdays, as the data shows significant increases in spot rates in both cases. Regarding the ML algorithm selection, the availability via open source libraries for easy adaptability on this and similar future cases was essential. The study includes simple, more interpretable ML models as well as less intuitive, but possibly more performant, ensemble learning methods that are built from a set of simple base models. Since neural networks are also popular for ML based prediction tasks, a corresponding algorithm was included as well. The simple models Decision Tree (DT) and Lasso Regression (LR) are selected. The ensemble methods consist of the Random Forest algorithm (RF), Gradient Boosting (GB) and eXtreme Gradient Boosting (XGB) [33–35]. Multilayer Perceptron (MLP) is added as a neural-network based algorithm accessible in Scikit-learn.

4.4 Evaluation phase

Evaluation is done using several metrics measuring the prediction error for the target variable of the models for a given order. Performance metrics for regression models have been controversially discussed and employed in literature without finding a common agreement. Still, no consensus on the "best" metric has been achieved [36,37]. To obtain a more reliable evaluation, a combination of metrics should be applied [38]. Therefore, the mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE) and the coefficient of determination (R^2), are applied as performance metrics in this study. The MAE metric is easily interpretable for practitioners, since it provides a general and bounded performance measure for the model. The MAPE measures relative deviations and is applicable since the target variable contains positive values only. However, MAPE scores are biased towards favoring lower predictions [36]. Even though unrealistic outliers have been removed in the data preparation phase, FR/km shows distinct variance for short distance trips. To assess the ability of models to deal with this variance, RMSE is used as an additional metric. It is more sensitive to variance by giving higher weight to larger errors [38]. R^2 provides a high score, if the greater part of elements is predicted correctly, showing the model's ability to explain the target variable [39]. Additionally, the computation time for training and prediction is considered as a metric.

5. Results

The results of the modeling phase are evaluated in Table 2. The results of the 90/10 data split are compared to the performance in cross-validation to measure the generalizability of the ML models. The BM was also applied to predict spot rates in the different validation sets of each fold. In general, it can be stated that all ML algorithms outperform the BM in both 90/10 split and cross-validation. In most cases, cross-validation results show a larger MAE, MAPE and RMSE, while R^2 is decreasing.

Table 2: Results of modeling in a 90/10 split and with cross-validation (best three values in bold)

	90/10 Split					**Cross-validation**				
	MAE [€]	RMSE [€]	MAPE [%]	R^2 - Test	Time [sec]	MAE [€]	RMSE [€]	MAPE [%]	R^2 - Test	Time [sec]
DT	**0.109**	0.208	5.97	0.908	2.92	0.142	0.245	8.105	0.745	8.056
LR	0.198	0.301	10.12	0.808	**0.16**	0.176	0.280	9.912	0.680	**7.047**
RF	**0.105**	**0.185**	5.62	**0.927**	9.02	**0.124**	**0.208**	7.275	**0.807**	10.647
GB	**0.106**	**0.194**	5.61	**0.920**	5.21	**0.129**	**0.211**	7.533	**0.801**	**7.895**
XGB	0.115	0.198	6.07	0.917	**0.57**	**0.130**	**0.222**	7.570	**0.787**	**7.234**
MLP	0.129	**0.196**	7.16	**0.918**	7.19	0.179	0.270	10.763	0.663	10.138
BM	0.216	0.324	11.17	0.778	**0.05**	0.206	0.326	11.85	0.642	3.03

In the 90/10 split, RF shows the best performance of all ML algorithms regarding the MAE, with GB and DT being almost equally predictive. However, comparing the RMSE, performance of DT is substantially lower than RF and GB. Moreover, the superiority of RF over GB becomes clearer, when the RMSE is considered. This indicates more stable predictions by RF with less larger errors. LR reveals its limited applicability to non-linear data structures scoring the highest MAE and RMSE and a R^2 which is only slightly better than the BM model. MLP does not achieve the best scores for the MAE, but presents the third best RMSE. Regarding the computation time, ML algorithms are slower than BM due to the fitting process. XGB and LR achieve the lowest computation time of all ML models.

In cross-validation, the scores for all models worsen. Especially, the DT and MLP algorithms show substantial decrease in performance relatively to their score in the 90/10 split, indicating overfitting tendencies by both algorithms. Again, RF outperforms the other algorithms in most metrics. However, RF presents the worst computing time during cross-validation. XGB and GB show MAE and RMSE results within the range of RF and competitive computation times, making them suitable solutions, when computation time is of importance. Remarkably, LR is the only algorithms that performed better during cross-validation than in the 90/10 split. Yet, it is not competitive in terms of the MAE and RMSE.

Figure 1 shows the distribution of prediction error of the best performing algorithm (RF) as a function of distance. RF predicts especially the dominating long distance trips with high precision. With shorter distances the amount of orders as well as the precision declines. To quantify the potential of using RF, an average transaction in the data set with a distance of 295 km and a mean FR/km of 1.61 €/km is considered. This accounts for average costs of around 475€. Considering the cross-validated MAE of 0.124 €/km, the average deviation is +/- 36.68 € per transport. Using the BM approach, an average deviation of +/- 61.95 € was found. In daily operations, unexpected waiting times are another source for price deviations. For example, a minor delay of 30 min already may cause unplanned, additional charges of around 0.10€/km. Hence, a one-hour delay on an average transaction due to congestion in traffic or at the point of disposal leads to deviations of around + 59.00 €. Therefore, the application of ML, may reduce deviations caused by delays for future transactions.

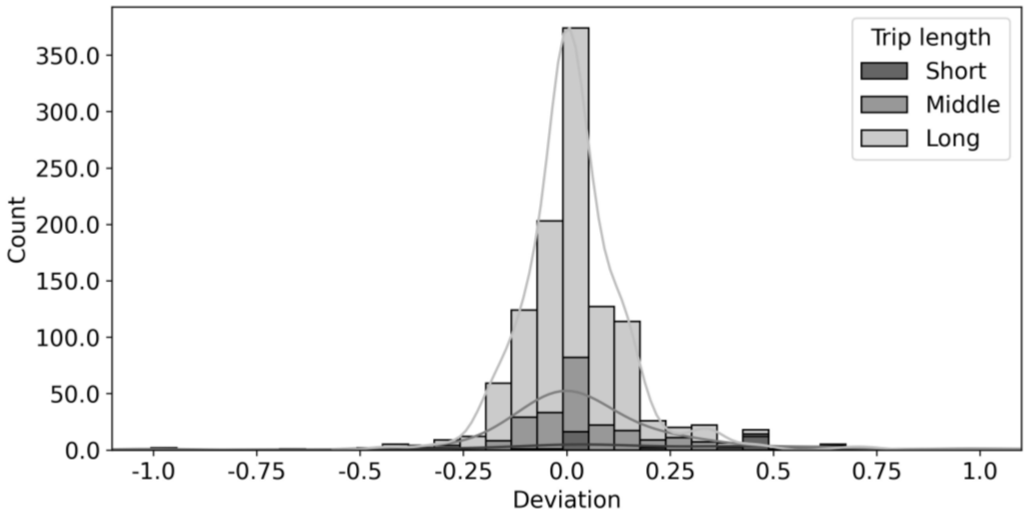

Figure 1: Distribution of prediction error of RF in the 90/10 split

6. Conclusion

The goal of this study was to demonstrate the applicability of ML algorithms for predicting spot rates for transports in the recycling industry. Data from a small broker in Northern Germany was used to train six ML algorithms. The predictive performance was benchmarked against a practical approach. In comparison, ML models outperformed the manually calculated benchmark method, proving the applicability of ML for spot rate prediction. From the set of ML algorithms, the Random Forest regressor minimized the prediction error the most.

The performance of ML on the prediction task in this study confirms promising application opportunities in real-world settings. In fact, performance is likely to improve during operation as more data is gradually fed into the model [32]. Moreover, the prediction horizon will be shorter (1-4 weeks) in comparison to the scenario in the study. More recent data is likely to prove beneficial for the predictive performance of all models. Future research can be dedicated various areas. For example, during modeling, effects of weighting more recent data or excluding older data on model performance can be investigated. Also, more advanced algorithms may yield improved results. Furthermore, the scope of application can be expanded. The effects of a geographical extension on the approach could be explored. Cooperation with other market participants offers opportunities to enlarge the database and improve the basis for modeling. The study not only built a foundation for ML application for spot rate prediction in the recycling industry. Rather, this study sets a starting point for further exploration of ML's predictive potential for price prediction in the transportation industry in research and practice.

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