Improving the Forecast of Freight Transport Demand Using Machine Learning and Time Series Methods

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Abstract

Previous research at ETH Zürich (Moll 2012b) already found that freight railway undertakings could increase their efficiency by far, by integrating demand predictions into their regular planning process. The shippers, as main sources of the demand data, often do not have their own forecasts, which have been done in an appropriate way, or are not willing to provide their forecast data to the railway undertakings. So the freight railway undertakings have to find other sources to enhance their own demand forecasts.

The railway undertakings have a lot of detailed data from former transports such as the “Wagenverlaufsdatei” (wagon run data), which contains a dataset for each transported wagon containing its origin, its destination, the demand date, the transported type of goods, the shipper, the route and the type of wagon used for the transport. One promising approach is to exploit time series methods and machine learning algorithms to forecast the demand using this existing data. The project presented here would therefore contribute a novel new field of application for existing machine learning and time series methods.

In other fields of transport demand forecast, for example in passenger demand forecast and in traffic flow forecasts on highways in Switzerland (a previous project completed by ZHAW) these methodological approaches have already shown good results. So in this project, which has just been started, ETH Zurich, Institute for Transport Planning and Systems and ZHAW Wädenswil, Institute of Applied Simulation, are testing a broad range of machine learning and time series methods for forecasting freight demand to enhance the efficiency of rail freight undertakings. This evaluation will include the identification of driver variables for freight demand depending on the type of goods, which are transported. The methods will then be further developed to include these driver variables and then the effect that the application of these methods could have on the efficiency of railway undertakings will be investigated. So this research will fill a gap in current knowledge as until now, only a small number of methods have been tested on limited data. This project would contribute to this field of knowledge by providing a thorough review and evaluation of a broad range of possible methods which could be applied to freight demand forecasting.

The wagon demand data for each day of one year (2012) has already been obtained from SBB Infrastructure. As a proof of concept, a simple neural network and a ARMA(5,5) model have been used to forecast the demand for the last 60 days, using the rest of the year’s data for training the methods. The results from these methods are presented here, but we expect to develop methods which are better suited to the problem and to obtain better results as the project, which is still in the very early stages, progresses. As we only have a few preliminary results so far, the main purpose of this paper is to present the project and the ideas behind it.

Keywords

Freight transport demand – Prediction – Machine learning – Time series methods

1. Introduction

Freight rail undertakings could increase their efficiency if they had good demand forecasts. In this project, which is planned as a collaborative project between the Institute for Transport Planning and Systems (IVT) at ETH, Zürich and the Institute of Applied Simulation (IAS) at ZHAW, Wädenswil, we plan to develop methods for forecasting freight demand. It ties in existing research at both institutions which optimally complement each other for the purpose of this project. The overall goal of this project is to substantially improve short-term and mid-term freight transport demand forecasts by employing machine learning and time series methods. The project thus aims to close a gap between the demand for reliable forecasting methods in practice and an underdeveloped field in basic and applied research.

1.1 Literature review

1.1.1 State and state-of-the-art in the operative field

For logistics companies, demand forecasting is important to reduce cost, improve efficiency and advance service quality (Yang 2010b). The role of freight transport as an important part of the day-to-day activities for business and people is still increasing, especially if we analyse the recent trends of e-commerce, economic globalization, high-tech warehousing and just-in-time production systems (Ibeas 2012). Whereas in the past logistics operations required lengthy and time-consuming interactions between all parties concerned, new web-based technologies enable much more reliable transport management. Advances in telecommunications and information technology have given companies the means to manage the movement of goods over long, often circuitous routes (Tavasszy 2012). However, transport still represents a considerable component of production costs for many industries (Hovi 2011). The growth and globalization of international trade mean that trade patterns and transport markets are changing. If investment is to be assessed so infrastructure supply can be matched to demand, forecasting freight flows is critical (Lyk-Jensen 2011). It is also fundamental to have methods and models to allow an assessment of policies and measures that can be implemented by local administrators in order to make freight mobility more sustainable (Ibeas 2012). Volumes of goods shipped by roads and railroads are predicted to increase by 98% and 88% respectively by 2035 (Chow 2010). This growth in freight transport is expected to greatly outpace growth in passenger transport. An increase in freight transportation results in the need to accurately estimate the movements of goods as well as to forecast the expected future truck and rail and underlying commodity flows. In the past, however, many state and local agencies have not devoted enough attention to forecast the movement of goods on transportation networks. The three main reasons for this are:

- Insufficient available freight related data sources
- Less practical experience concerning freight forecasting than that related to the movement of passengers
- Currently developed freight models appear to be sophisticated but are highly limited in terms of available input data (Yang 2010b).

Another complicating factor is that the ability to forecast freight transport, especially by rail, differs strongly by shipper and commodity type (Moll 2012a). Accurate demand forecasts are critical for logistics companies to improve their efficiency of their resource usage.

1.1.2 State-of-the-art freight demand forecasting research

Many methods for freight transport forecasting have originally been adapted from forecasting models for other forms of transport. However, obvious differences between freight transport and passenger transport hinder a straight-forward methodological transfer. A recent freight model literature review can be found in (De Jong 2004). Modelling techniques for forecasting commodity flows include some applications of artificial neural networks (ANN), general equilibrium models (input-output models), optimization models and gravity models (Lyk-Jensen 2011). To some degree, they also include time-series models and multivariate regression analyses (Wang 2013). In (Goulielmos 2011), autoregressive moving average (ARMA) models were compared to Neural Networks for freight shipping prediction. In (Lyk-Jensen 2011), Lyk-Jensen uses a dynamic three-ways-effect gravity equation to forecast trade flows in the EU15 countries and also in Switzerland and Norway 1967-2002. It was used to forecast yearly commodity flows. In (Wang 2013) Wang et al. construct an asymmetric probabilistic fuzzy set and apply it to freight turnover forecasting. In (Li 2013) Li uses Holt exponential smoothing and Brown exponential smoothing to forecast some freight turnovers for 2006 to 2010 from data from 1996 to 2005. In (Goulielmos 2011), Goulielmos and Psifia show that some maritime freight time series don’t follow the normal distribution but rather leptokurtic distributions. They then go on to forecast some freight turnovers using the V-statistic. In (Tonghe 2010), Tonghe et al. use a Grey Neural Network model to forecast future freight volumes. In (Gao 2010), Gao et al. investigate forecasting road freight volumes by grey system forecasting, neural networks and support vector machines and support vector machines give the best results. In (Wang 2012), Wang et al. develop a hierarchical regression model with random intercepts to evaluate the relationship between truck freight demand and influential factors including population, the number of firma and median income at the county-level. In (Xiaoqing 2012), Xiaoquing applies Grey system theory to predict regional logistics demand. In (Yang 2010a), Yang et al. apply a Grey system theory time series prediction model to predict logistics demand and it is shown to give better results than

ARMA. In (Hua 2009), Hua et al. apply Grey system forecasting to forecast freight demand in China. In (Garrido 2000), Garrido et al. apply the multinomial probit model to analyse and forecast freight transportation demand. The model predictions were tested using the non-parametric Spearman's rank correlation test and significant rank correlation was found between the forecast shipments and the actual shipments for each subsample used.

There have been a small number of papers published on possible influencing factors (driver variables) for freight demand. For example, Blanquart et al. (Blanquart 2012) who reviewed the impacts on transport demand from a supplier to a retail controlled supply chain. In Maes et al., (Maes 2012), a conceptual freight transportation framework was proposed, which included a market module (supplier choice, quantity to be purchased), a logistic module (considerations of carriers and forwarders) and a network assignment module (equipment and link capacities). Tavasszy et al. (Tavasszy 2012) published a review of how service and cost drivers of changes in logistics networks affect freight transport.

2. Methods

Two simple methods were chosen to get some preliminary results. No driver variable data was included. Further methods will be the objects of investigation during the course of this project and it is expected that more specific methods better suited to freight transport forecasting will be found, which take driver variable data into account.

2.1 Artificial neural network

Artificial neural networks are computational models inspired by animals central nervous systems, especially the brain. These models are capable of machine learning and pattern recognition. They consist of a network of interconnected computational units, so called neurons, which compute values by feeding information through the network. Multilayer perceptrons are one class of neural networks that can be used to approximate any function, especially nonlinear ones (Haykin 1999).

Multilayer perceptrons consist of a series of layers, each containing a number of neurons. Each neuron has a weight and multiplies its inputs by that weight and sums them before sending the result to its output. This output is then scaled using a defined function, often a sigmoid function. The first layer has connections from the network inputs. Each subsequent layer has connections from the previous layer, with each neuron being connected to each neuron in the previous layer. The final layer produces the network's output. When the network is trained using known outputs for given inputs, the weights of each neuron are changed so that the network output is as close to the known output as possible. When the network has been trained, it can be used to predict new outputs from a set of input data.

In the work presented here, a feedforward multilayer perceptron with a single layer containing 20 neurons is used. There are 5 inputs which are 5 versions of the time series with time lags from 1 to 5. This was programmed using MATLAB (MATLAB R2012b, The MathWorks Inc., Natick, MA). The output from the single layer is multiplied by a sigmoid function, which is the MATLAB default.

2.2 Autoregressive moving average model (ARMA(p,q))

This model can be used to model consists of two parts, an autoregressive (AR) part and a moving average (MA) part (Box 1976). They can be used to model any weakly stationary time series, i.e. time series with an autocovariance which does not vary over time (i.e. the time series contains some periodic patterns). It is assumed that freight transport demand data contains some periodic patterns as, for instance, the demand will probably always be less at weekends compared to week days.

An autoregressive model of order p (AR(p)) is given by the following equation;

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

Where c is a constant, φ_i are parameters which are calculated when the model is trained and ε_t are random variables (white noise).

A moving average model of order q (MA(q)) is given by the following equation;

$$X_t = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Where, again, ε_t are random variables (white noise) and θ_i are parameters which are calculated when the model is trained.

The combined autoregressive moving average model (ARMA(p,q)) is given by;

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Once the parameters in the model are set by training using known values, the model can be used to predict the new values in a time series from the previous values.

In the work presented here, an ARMA(5,5) model is used. This was programmed using MATLAB (MATLAB R2012b, The MathWorks Inc., Natick, MA). The p and q values were set to 5 in order to be comparable with the neural network, which used 5 time lags.

2.3 Root Mean Square Error (RMSE)

Root mean square error was used to determine how well the two methods performed. This is a measure of the difference between the predicted output and the actual values. It is given by;

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(X_i^{predicted} - X_i^{actual}\right)^2}{N}}$$

Where $X_i^{predicted}$ are the predicted values, X_i^{actual} are the actual values and N is the number of values. RMSE was chosen as it is a simple measure of goodness of fit and we are interested in acquiring some initial results using simple methods. Other possible measures, for example, coefficient of determination (R^2), have a more complicated definition but further measures will be investigated as part of this project.

2.4 Demand data

Data were acquired from SBB infrastructure which gave a list of wagons travelling in Switzerland for each day of 2012. The data file contained one line for each wagon and gave the date, the codes for the starting and finishing stations and the weight and length of the wagon. Example data file entries can be seen in Figure 1. The number of wagons travelling each day was counted using a program written in Java and it was this time series of numbers of wagons which was used for the demand forecast.

Figure 1 Example data file entries

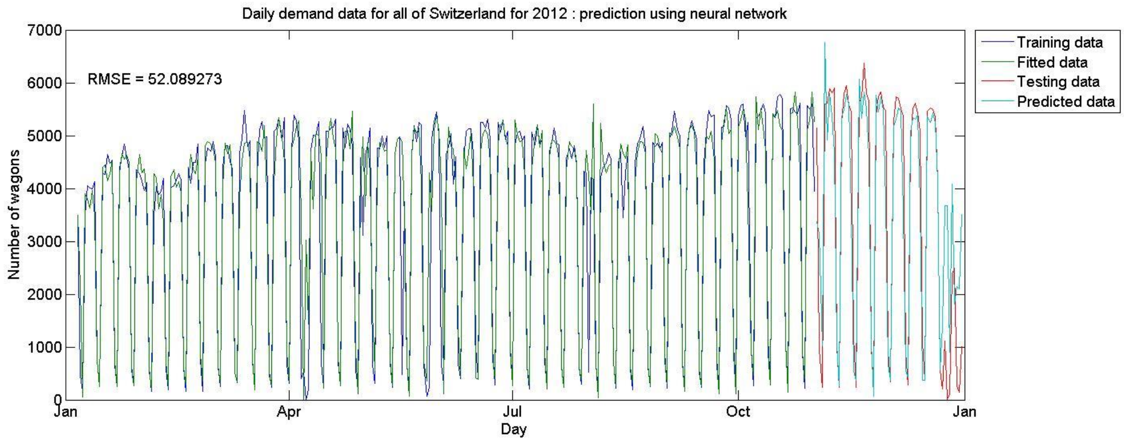
```
"GV_Art_neu";"Datum_VS";"UICBahn_VS";"BhfNr_VS";"BhfNr_EM";"Transport_Art";"B
ef_Art";"Netto_Gew";"Brutto_Gew";"vonzelle";"nachzelle";"Wagenlaenge";"Tara_Wagen";"
Typ";"netto_neu"
1;1.1.2012 00:00:00;85;133;10041;18;10;0;85000;85000133;324006;1890;85000;3;1
1;2.1.2012 00:00:00;83;17194;915207;10;18;11000;30500;322005;259;1960;19500;4;10
1;2.1.2012 00:00:00;83;17194;915207;10;18;11500;24000;322005;259;1510;12500;4;10
1;2.1.2012 00:00:00;83;17194;915207;10;18;11500;31600;322005;259;1970;20100;4;10
1;2.1.2012 00:00:00;83;17194;915207;10;18;20732;49732;322005;259;2960;29000;4;20
```

3. Results

The demand data was re-formatted to give the number of wagons which travelled each day for every day of 2012. The data was split into a training set and a testing set. The testing set was data from the last 60 days of 2012 and the training set was the remaining (306 days) data. RMSE values were calculated for the predicted values compared with the testing set values.

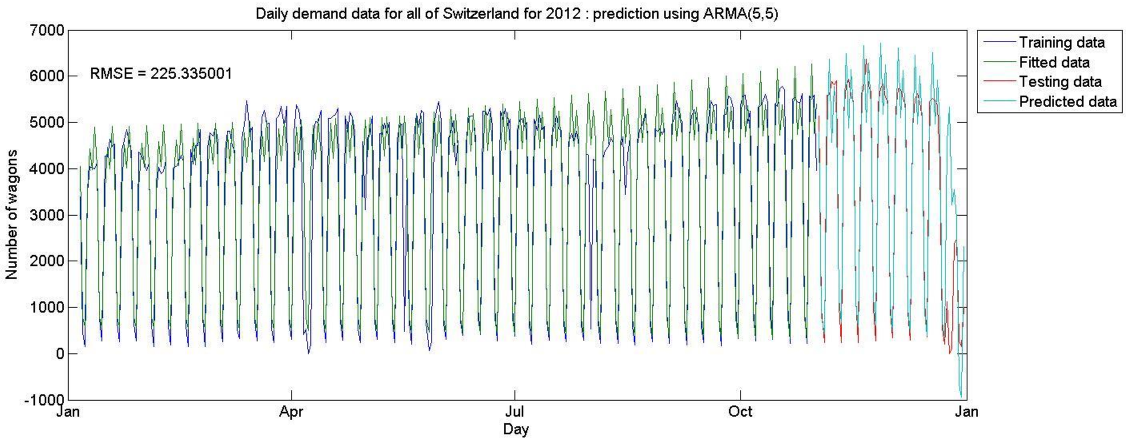
First a feed forward neural net, as described in Section 2.1, was used. The results can be seen in Figure 2 below and the RMSE value was 52.089273.

Figure 2 Results using feed forward neural network



Next, an ARMA(5,5) model, as described in Section 2.2 was used. The results can be seen in Figure 3 below and the RMSE value was 225.335001. The ARMA model predicted some negative (unphysical) results at the end of the testing phase.

Figure 3 Results using ARMA(5,5) model



4. The ongoing research project

To prove the feasibility of time series methods to predict the demand in rail freight a collaborative project between the Institute for Transport Planning and Systems (IVT) at ETH, Zürich with knowledge in the field of rail-freight and the Institute of Applied Simulation (IAS) at ZHAW, Wädenswil with experience in the field of demand prediction is implemented. It ties in existing research at both institutions which optimally complement each other for the purpose of this project. The overall goal of this project is to substantially improve short-term and mid-term freight transport demand forecasts by employing machine learning and time series methods. The project thus aims to close a gap between the demand for reliable forecasting methods in practice and an underdeveloped field in basic and applied research. We have applied for SNF (Swiss National Science Foundation) funding for this project.

5. Discussion and Conclusions

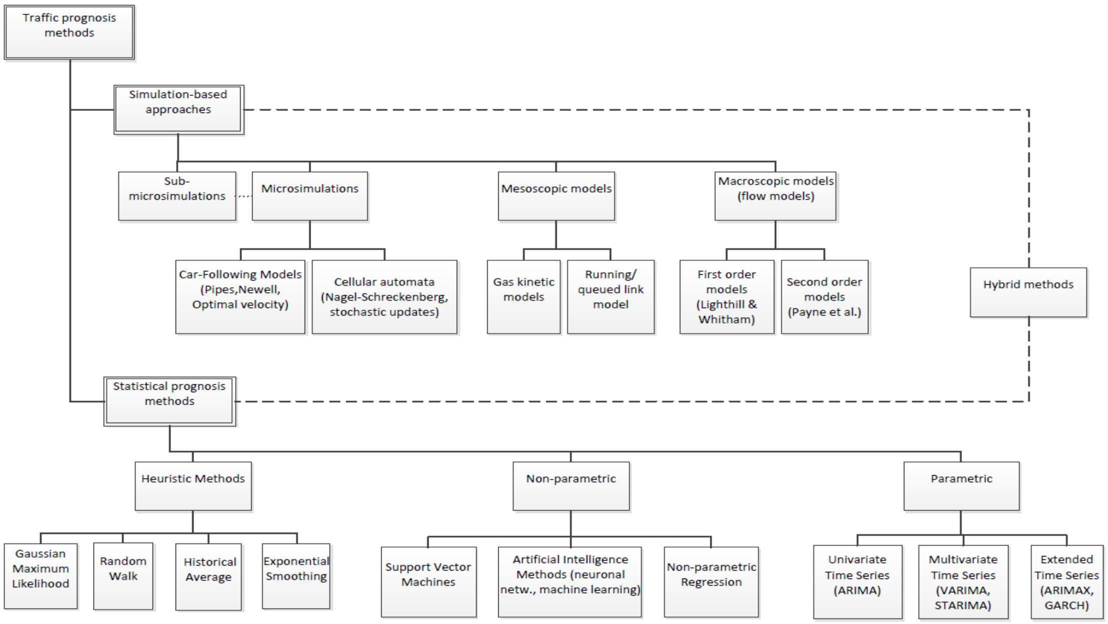
We have presented our planned project on freight transport demand forecasting. Although this project is still at a very early stage, we have already acquired the demand data for one year from SBB infrastructure and have used it to test two simple prediction methods.

Although the two methods which we tested were very simple and did not include any driver variable data, the general periodic pattern was reproduced for the last 60 days of the year. These preliminary results thus already point out the potential of time series and machine learning methods for freight transport demand forecasting and encourage further research.

The RMSE values were 52.089273 for the neural network and 225.335001 for the ARMA model. Therefore, the neural network performed better than the ARMA model. By visually inspecting the results, in can be seen that the patterns in the data were generally reproduced even though all the values were not totally accurate. One problem was that the ARMA model predicted some negative numbers of wagons at the end of the testing phase. This is a weakness of this method. The methods also tended to be less accurate during the last days of the prediction, this could have been partly due to the influence of the Christmas holidays which supports the fact that external factors need to be included.

We will be able to improve significantly on these results. We will test a larger number of methods and will include driver variable data. We will also acquire more demand data from railway undertakings and will test the methods in a number of different case studies. Some of the methods which we may investigate will be taken from the work done by ZHAW on motorway traffic forecasting (Burkhard). A diagram showing methods found in this work is shown in Figure 4 below. Methods which could be used are, for example, Gaussian maximum likelihood, support vector machines, non-parametric regression or multivariate time series methods (e.g. VARIMA).

Figure 4 Overall grouping of and relationships between different methods for traffic forecasting, according to (Burkhard)



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