Forecasting freight demand at intermodal terminals using neural networks – an integrated framework

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1. Introduction

In a general sense, freight ***intermodal transportation*** refers to the movement of cargo using more than one transportation mode for its journey and requiring processing (transhipment, classification, consolidation, etc.) at associated intermodal terminals. A significant proportion of such intermodal, or multi-modal, transportation is performed by using containers. Intermodal transportation is therefore often equated to container transportation and carriers operating container-based transportation services are identified as intermodal carriers.

This is particularly the case in North America where railways have created intermodal divisions focused on the efficient container transportation for the local and international markets. An innovative service mode proposed and introduced by one of the main Canadian rail carriers is analysed here. It is the *scheduled-with-bookings* system, which operates regular scheduled services and requires customers to book space in advance for their freight. The pool of advantages brought by the new way of operating intermodal rail services is twofold. First, as far as the carrier is concerned, operating costs are diminished, since a "full asset utilisation" policy – as a cost minimising strategy, based on the maximum utilisation of the assets (power engines, rail cars, labour forces) allocated to the services – can be much more easily applied, due to the cyclic and constant capacity mode of operation. The company runs the same service – in terms on total capacity, schedules, and train *block* composition (groups of rail cars that will travel together on a given origin-destination) – on a daily basis. Second, as far as the customers are concerned, thy benefit (once they get used to the new operating fashion) from increased reliability, regular and predictable service and, eventually, better price. This type of system could be successfully implemented and applied to the entire service network of the rail carrier, for the domestic and export traffic. The difficulty in extending this type of service to include the import international traffic rises from the important uncertainties associated to the time import containers stay in ports, between their arrival by ship and their departure loaded on rail cars.

In multi-modal/intermodal chains, ports constitute the connection points between maritime and land transportation systems. Vehicles and containers undergo complex series of operations at those terminals, which significantly impact the efficiency and cost of freight intermodal transportation. As ports constitute the main continental gateways in general and for North-America and Canada in particular, Custom and Immigration controls constitute an integral and critical part of the transfer process containers must go through. In the contemporary context of tight security, these activities may add significant complexity and delays to port operations, which makes the time containers spend in port before leaving by another transportation mode even more difficult to predict.

These being said, it is clear that for the next carrier in the transportation chain, especially when it is providing *scheduled with bookings* services, reliable forecasts with respect to the quantities and types of containers released from port terminals on a daily basis becomes a critical need. In this context, the research work presented here deals with designing a forecasting methodology, based on neural networks, for intermodal transport demand (import containers released daily from port terminals). The present study focuses on maritime – rail container transfer. One Canadian important port and data from on major rail intermodal Canadian carrier are used here, as an illustration of the applicability of the developed methodology.

2. Forecasting freight demand at intermodal terminals – problem characterisation

The main function of a container port terminal is to provide transfer facilities for containers between sea vessels and land transportation modes, trucks and rail in particular. It is a highly complex system that involves numerous stakeholders (e.g., port and terminal authorities, shipping companies, railroads, motor carriers, brokers, shippers, forwarders, and regulatory agencies), pieces of equipment, operations, and container handling steps. Beyond the number and variety of stakeholders and activities, the complexity is mainly due to the complex physical and informational interactions among stakeholders, on the one hand, and the different planning and operational processes taking place at the terminal, on the other hand (Crainic and Kim 2005, Steenken et al. 2004, Vis and Koster 2003).

Ship arrivals in port are off-schedule quite frequently, which implies pre-planned in-terminal operations have also to be revisited on a daily basis. Weather conditions affect not only ship arrival time in port but in-terminal operations as well: e.g., in winter time important delays in container manipulations may appear due to snow storms or very low temperatures. Another disruption factor is the empty cars daily availability: if not enough high and low capacity cars are available (high or low capacity refers to the maximum weight permitted) for loading the containers which have already cleared all the Customs controls and other required inspections (containers that are ready to go – which we refer to as daily demand), the demand cannot be satisfied thoroughly – not all the containers that are ready for departure that day can be loaded on cars and sent to the corresponding rail transportation service. This, of course, implies an overhead in demand for the next day. The day of the week is an important explanatory variable of the demand model with respect to the labour force daily availability: during weekends this availability is diminished or is more costly for the Terminal Administration/Management.

All those uncertainty factors generate high variability to be associated to the container transfer process in port terminals, variability that clashes with the regularity and rigidity of the intermodal rail service in place. It becomes thus clear that, in order to operate efficiently this type of system, the need for reliable forecasts with respect to the container release time from port terminals is critical. Those predictions will be next used within methods that dynamically adjust the transportation plan to demand while continuing to operate according to the full-asset-utilisation policy of the rail carrier. As we are talking about dynamic adjustment, we are obviously concerned with a dynamic way of updating the forecasts, using the latest information available in the system (including new data, informational or structural changes in the transfer process etc.).

The problem of forecasting demand in general is old and well established. Results in econometrics, statistics, and, more recently, in artificial intelligence (neural, fuzzy approaches, expert systems etc.) offer a large spectrum of ways to tackle the problem. Nevertheless, there is no general forecasting methodology that can be applied to solve all the diverse situations one may be confronted with. When the process for which the forecasting is needed is very complex, difficult to model, and is performed in a dynamic environment, traditional statistical or econometrical techniques become very much inappropriate. Econometric and time series models are very data demanding and are difficult to use in a dynamic context were data is continuously updated. They are estimated using a particular sample and even if they perform very well for this sample, they do not adapt easily to changing structural conditions. Furthermore, their adaptation/updating procedure may be difficult to implement for non-specialist end-users. Finally, such methodologies have not been developed for generating forecasts to be used in real-time planning models.

On the other hand, several studies reviewed in the following section highlight good performances achieved by dynamic learning methodologies, such as *Artificial Neural Networks* (Hykin 1994, Potvin and Smith 2001), in time series prediction when compared to classical forecasting techniques. This type of forecasting methodologies seems to be appropriate for our goals. The forecast updating process is robust (*graceful-degradation* property) and can be performed in a flexible (i.e., different input data) and repetitive (e.g., on a daily basis) way. Another advantage of this approach is its adaptability to change. The neural network can be modelled to take into account the dynamics and evolution of a time-dependent system and may be set up to automatically and dynamically update itself.

Artificial Neural Networks (ANNs) can be seen as tools for non-linear modelling of complex systems by *learning*. They may be seen also as a non-linear extension of statistical methods, without making any hypothesis about the existence of some particular structure in the data. *Supervised learning* is performed based on a set of input-output examples that are presented to the neural network. The input data is fed to the neural network, which adapts its parameters (based on well defined algorithms) in order to minimize the error between its output and the expected output (the one corresponding to the input data). Thus, after a certain number of training epochs (cycles), the network should present the capacity of *generalization*, which is the ability to compute satisfying outputs from inputs that were never presented to the network before.

We are concerned here with designing a general forecasting methodology, based on neural networks, for intermodal freight transportation demand (containers released from port terminals) in order to improve the efficiency of containers transportation on an intermodal chain, within the framework of a *scheduled with bookings* rail operations management system. As a case study, the forecasting framework proposed is applied to one important Canadian port, for illustration of its performances. The forecasting module is easily adaptable to a dynamic operation mode to account for the continuously changing operations of an intermodal port terminal.

3. Literature review

Due to lack of space, we only emphasize the very good performances of neural network-based forecasting compared to other (conventional) methods (e.g., Dharia and Adeli, 2003; Huisken and van Berkum, 2002; Sayed and Razavi, 2000; Abdelwahab and Sayed, 1999; Faghri *et al*., 1999; Park and Rilett, 1998; Bansal *et al.,* 1998, etc.). We did not find any reference relevant to the specific problem addressed in this presentation. Nevertheless, similar problems (e.g., prediction of truck-traffic volumes) were approached using neural network models (Al-Deek 2001, Klodzinski and Al-Deek 2003, Sarvareddy *et al.* 2003). This encouraged us to envisage the present development.

4. General description of the proposed approach

An important phase of data collection and pre-processing was performed before the neural network could be calibrated and trained, and its prediction capabilities could be assessed. Data consisted in historical records on the arrival dates of vessels in port and the corresponding total import volumes, as well as on container volumes (loaded on rail cars) departing daily from the port terminal.

Different learning parameters have been evaluated in order to retain the best fitted ones for the described prediction problem. The preliminary best results have been obtained by using the resilient propagation learning algorithm, which gives a training error very close to zero and a very good generalisation performance (9% of error for a single output).

Quality and quantity of data are widely recognized as important issues in the development of neural network models (Lyons et al., 1998). Using real data collected from the field, instead of simulated data, renders our research even more difficult and challenging. Nevertheless, the use of real data in the presented study enhances the importance of the results obtained.

For the *neural network structure definition*, different parameters needed calibration: type of network (feed-forward, recurrent etc.), number of hidden layers, number of nodes at each hidden layer, weights initialisation, activation function. The neural network type retained is of the feed-forward type. Several learning algorithms were compared: standard backpropagation, batch backpropagation, backpropagation with momentum, resilient backpropagation. As mentioned above, the best results with respect to the speed of convergence for the learning pattern sets and with respect to the generalisation capabilities were obtained with the *resilient backpropagation* algorithm. This algorithm is used for feed-forward networks and is an adaptive learning algorithm which avoids the problem of "blurred" adaptation process (Riedmiller and Braun, 1993), by changing the size of weight-updates without considering the size of the partial derivatives, but only their sign (positive or negative). The supervised *training algorithm* had to be properly calibrated as well, which implied the tuning of several other parameters: learning rate, number of training epochs, error measure etc. A thorough study was required and the results will be presented.

The prediction mechanism works as follows: given the current day information (ship arrival, quantities of containers for particular destinations, historical arrival quantities etc), the number of 20 and 40 feet ramped containers that would leave the port the following (one, two, or three) day(s) is predicted. In our study, the prediction capabilities of the neural network model were validated using data from an important Canadian port for five months (January to May). The same model, i.e., the same trained neural network, should give good results when used with new data sets for the same terminal and the same ranges of the explanatory variables used.

If the ranges of those variables are subject to change, due to new port terminal organisation, new vessels arriving in port, new ranges of container quantities observed, and so on, the model can be dynamically updated. Using newly registered data, new learning and validation data sets must be built and used to train the neural network. It is noteworthy that this means that one does not need to change neither the structure of the neural network, nor that of the learning algorithm and parameters.

The learning process takes only a few minutes on a medium-powerful computer. Thus, generating new data sets for use with the neural network could be performed automatically and the model could thus be "updated", or retrained, daily. Such a dynamic adjustment could be implemented as long as the behaviour of the system is reasonably stable. When, on the other hand, important structural changes in the process are observed (i.e., the explanatory variables would change), a thorough calibration phase should be performed with newly collected data.

5. Conclusions

Different learning parameters have been evaluated. Best results were obtained by using the resilient propagation learning algorithm, which displays a training error very close to zero and a very good generalisation performance when applied on a *zero-days delayed prediction scheme* (forecasting volumes for the same day as the current day available information). When applying the same type of neural network trained for a *two-days delayed prediction scheme* (forecasting volumes for the following second day using the current day available information) the generalisation performances are (as expected) slightly lower but still very promising.

We will present the general problem and methodology, the case study and the particular implementation, and the experimental framework. We will discuss results and a number of scenario analyses. We will highlight the abilities of the proposed methodology to use broad sets of information, providing the capability to integrate newly available data. Thus, this powerful and flexible methodology can be adapted to processes that dynamically adjust the offer of service to demand.

References

Abdelwahab W., and Sayed T., Freight mode choice models using artificial neural networks, *Civil Engineering and Environmental Systems* 16(4), 1999, pp 267-286

Al-Deek, H.M., Which Method is better for Developing Freight Planning Models at Seaports: Neural Networks or Multiple Regression?, *Journal of the Transportation Research Board* 1763, December 2001, pp. 90-97

Bansal, K., Vadhavkar S., and Gupta, A., Neural networks based forecasting techniques for inventory control applications, *Data Mining and Knowledge Discovery* 2(1), 1998, pp. 97-102

Crainic, T.G. and Kim, K.H., Intermodal Transportation, in *Transportation, Handbooks in Operations Research and Management Science*, C. Barnhart and G. Laporte (eds.), North-Holland, Amsterdam, forthcoming, 2005

Dharia A, and Adeli H., Neural network model for rapid forecasting of freeway link travel time, *Engineering Applications of Artificial Intelligence* 16(7-8), 2003, pp. 607-613

Faghri, A., Aneja, S., and Vaziri, M., Estimation of percentage of pass-by trips generated by a shopping center using artificial neural networks, *Transportation Planning and* Technology, 22 (4), 1999, pp. 271-286

Huisken, G. and van Berkum, E, Short-Term Travel Time Prediction Using a Neural Network, in *Proceedings of the 13th Mini EURO Conference*, Polytechnic University of Bari, 2002

Hykin S., *Neural Networks*, Macmillan, 1994, ISBN 0-02-352761-7

Klodzinski, J. and Al-Deek, H.M., Transferability of an Intermodal Freight Transportation Forecasting Model to Major Florida Seaports, *Transportation Research Record* 1820, 2003, pp. 36-45

Lyons, G.D., Hunt, J.G., and Yousif, S.Y., Factors Influencing the Performance of a Neural Network Driver Decision Model: A Case Study Using Simulated Data, *Neural Networks in Transport Applications*, edited by V. Himanen, P. Nijkamp, A. Reggiani and J. Raitio, Ashgate, 1998, pp. 229-248

Park, D.J. and Rilett, L.R., Forecasting multiple-period freeway link travel times using modular neural networks, in *Land Use and Transportation Planning and Programming Applications*, *Transportation Research Record* 1617, 1988, pp. 163-170

Potvin, J.-Y. and Smith, K.A., Artificial Neural Networks for Combinatorial Optimization, rapport CRT-2001-02, Centre de recherche sur les transports, 2001

Riedmiller, M., and H. Braun, A direct adaptive method for faster backpropagation learning: the RPROP algorithm, *Proceedings of the IEEE International Conference on Neural Networks*, 1993

Sarvareddy, P., Al-Deek, H.M., Klodzinski, J., and Anagnostopoulos, G., Evaluation of Two Neural Network Methods for Generating Heavy Truck Trips at Port Canaveral using Vessel Freight Data, submitted to *Transportation Research Record*, 2004

Sayed T, and Razavi, A., Comparison of neural and conventional approaches to mode choice analysis, *Journal of Computing in Civil Engineering* 14(1), 2000, pp. 23-30

Steenken, D., Voß, S., and Stahlbock, R., Container terminal operation and operations research – a classification and literature review, *OR Spectrum* 26, 2004, pp. 3-49

Vis, I.F.A. and de Koster, R., Transshipment of containers at a container terminal: An overview, *European Journal of Operational Research* 147, 2003, 1-16