OPTIMIZING HINTERLAND TERMINAL OPERATION USING SIMULATION AND NEURAL NETWORKS

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ABSTRACT

In this paper we investigate a major problem in hinterland terminal optimization. Terminal operation consists of a series of interdependent activities and decision problems. The overall performance in the terminal operation is influenced by operation's efficiency and differs for different terminal design, workload and policy. We use a methodology that combines simulation and neural networks and that can be used to define, with respect to terminal design and workload, the best operating policy.

Keywords: Simulation, Neural Networks, Hinterland Terminals, Optimization.

1. INTRODUCTION

Hinterland terminals enable the transhipment of load units between various modes of transport (ship, truck and train) and play a significant role in intermodal freight transport. Since intermodalism in general has become an important issue (Bontekoning, Macharis, and Trip 2004), hinterland terminals are looking to increase their effectiveness and efficiency.

Terminal operation consists of a series of interdependent activities which describe the container flow through the terminal. An overview of container terminal operation, involving ship, train and truck transport, is given by Vis and de Koster (2003).

Terminal activities take place in three major areas: the interchange area where transport modes enter the terminal, the transhipment area where the loading and unloading is done and the yard area where load units are stored. The overall performance in terminal operation is influenced by the operation's efficiency of all these areas. While optimizing terminal operation, one therefore, needs to take into consideration all existing interdependencies. For example, the scheduling problem for loading and unloading activities of a train is highly related to the storage allocation problem in the yard and to the track allocation problem of the rail interchange.

Further, terminal optimisation has to take into account decisions of different time horizon (Meersmans and Dekker 2001). While strategic decisions focus on terminal design, tactical and operational decisions deal with operating policies, as the assignment and scheduling of terminal resources. Defining layout and equipment of a terminal has therefore a direct impact on the efficiency of the chosen policies. Moreover, the decision on which policy to choose is highly influenced by the predefined terminal design.

Finally, terminal performance is also affected by the actual workload. Features as arrival pattern, average storage time, load unit characteristics or modal split determine, in combination with terminal design, the utilization degree of the resources. Different combinations of terminal design and workload (denoted as terminal configuration) can in fact have different impacts on terminal performance.

Due to the complexity of terminal operation and to the various existing interdependencies a systematic approach is needed. In this paper we propose a method that can be used to determine, with respect to the predefined configuration, which policy would result in a favourable terminal performance.

Most available research focuses on one specific terminal area or decision problem, allowing thus only for partial optimization (Steenken, Voß, and Stahlbock 2004). Some research, mostly simulation based, is done on the overall performance of container terminals. In fact computer-based simulation is particularly apt to describe the inner workings of a terminal (Rizolli, Fornara, and Gambardella 2002) and can therefore be used to assess the impact of a specific configuration and policy on terminal performance. Because simulation is mainly used to analyze the outcome of predefined scenarios, fundamental insights into factors affecting terminal performance are still lacking.

The method that we propose combines simulation with optimization and outlines the functioning of container terminal systems. Due to the great number of parameters and constraints describing the terminal operation, we do not want to explicitly define and explain the existing interdependencies. In fact, we choose to approximate the function linking terminal configuration and policy to terminal performance by implementing a neural network. The neural network uses simulation results from scenario analyses to estimate a non-linear function representing the terminal system.

2. PROBLEM STATEMENT

Terminal managers face a complex decision making environment where a large set of strategic, tactical and operational decisions have to be solved.

One of the most crucial decisions is related to allocation of storage capacities to the incoming containers. In fact, storage space is in most European hinterland container terminals a scarce good, and has therefore to be used efficiently. From the point of view of mere terminal processes, the storage area is used to bridge the time gap between arrival and departure time of a container. When a container is delivered for example by a train and the picking truck has not yet arrived, the container has to be lifted into the yard. This additional lift is necessary as the train has a limited time for the unloading process. The yard manager has therefore to make sure that for all arriving containers, an adequate storage space is reserved. Knowing that terminal operators often take considerable profits from the storage fees charged, it becomes clear that a balancing decision has to be solved.

Further, the goal of the yard manager is not only to provide for storage space, but also to do this efficiently. This means that the storage movement has to be done as fast as possible, to reduce the transport mode waiting time. Therefore, the storage allocation decision has to take into account the best equipment allocation and the best storage allocation. This means that the transport and lifting time of the container has to be optimized by allocating the nearest handling equipment and choosing the nearest storage spot which simultaneously reduces future unproductive moves. Whereas unproductive moves are defined as reshuffles, which are required to access another container that is stored beneath it. This implies that reshuffles occur only when removing containers from the stack.

Reducing the number of unproductive moves and minimizing the travel distance of the handling equipment consequently improves the container movement time, which reduces the residence time of the transport mode. A higher utilization rate of the yard however results in longer handling times, as the number of available storage spots is reduced. The main goal of the yard manager is therefore, to choose a storage strategy which matches the current terminal circumstances best.

During on-field visits and interviews with experienced yard manager, we observed several storage policies.

1. Avoid container stacking as long as the yard utilization allows for. If stacking is unavoidable choose from policy 2 to 4.
2. Choose nearest available storage slot without considering any stacking constraint
3. Choose nearest available storage slot while avoiding to stack on a container with an earlier expected pick-up time.
4. Prefer container stacking, while stacking only import containers with same arrival time and train number. Containers delivered by truck stock according to policy 3.
5. Prefer stacking and group all containers according to their destination and source.
6. Choose from policy 3 to 5 and segregate storage area according to container dwell time characteristics (storage or transshipment container).
7. Choose from policy 3 to 5 and separate import and export containers (import containers are delivered by train and export containers are delivered by truck and leave the terminal by train).

We further observed that yard manager mostly make decisions intuitively and can hardly describe their decision process or their motives. This is mainly due to the existing complexity and interdependencies in terminal operations. In fact, which policy to choose depends on the terminal configuration and applied operation strategies and workload (see table 1).

Table 1: Existing interdependencies

Factors		
terminal con-figuration	capacity	yard, tracks, truck gate, marshalling yard, equipment
	layout	yard, tracks
terminal workload	throughput	arrival rate, fluctuations, peaks, seasonality
	Interferences	train or truck delays
	container characteristics	length, stackable/not stackable, storage or transshipment containers, weight categories, road semi-trailer/swap bodies
operation strategies	equipment	allocation, scheduling, routing
	yard	allocation, marshalling, segregation
	truck gate	processing, truck parking
	tracks	grouping, pulsing, priorization
	operating hours	standard, extra hours

When choosing a storage policy one has there to take account of all factors describing the terminal. For example the yard capacity (defined by storage block characteristics as number of tiers, rows and sectors) is influenced by the arrival pattern of the containers and the container characteristics. In fact when the arrival rate and the ratio of non-stackable containers increase, the storage utilization increases and the container handling time also increases.

In order to define the best policy for a specific terminal, a decision support tool is needed. We tried to solve this problem by combining simulation and neural network methodology. Our goal is to use the capabilities of neural networks to generalize from examples, to develop a decision tool that can learn without any knowledge of the system and without any procedure formulation.

3. PROPOSED SOLUTION

Various applications of neural networks for optimization problems exist. This includes for instance transportation problems as Travelling Salesman Problems (Xu and Tsai 1990) or Shortest Path Algorithm (Zhang and Thomopoulos 1989; Soylu et al. 2000); scheduling problems (Vaithyanathan and Ignizio 1992; Johnston and Adorf 1992; Sabuncuoglu and Gurgun 1996.), combinatorial optimization problems (Lee and Sheu 1990; Sun and Nemati 2003) or dispatching problems (Vukadinovic et al. 1997; Ball 1996). We want to use neural networks to select an allocation procedure from a set of available techniques, by integrating it into a generic discrete event simulation. This approach can be classified as pattern prediction problem (Juhasz et al. 2003; Lazar and Pastravanu 2002)

The combination of simulation and neural networks is for several reasons beneficial. First the simulation of the terminal operations delivers a starting point for understanding the underlying processes. By modelling the different operations areas, one implicitly takes into account a great deal of the existing interdependencies. Further, the simulation can be used to deliver the necessary training data for the neural network. By changing step by step the simulation parameter, one can produce a great amount of example data. Finally integrating the output of the neural network into the simulation can help evaluating the performance of the neural network and can give more insight into its impacts on different terminal areas. Moreover, the integration of the neural network into the simulation can be used to dynamically define the best policy for the ongoing system status.

As system parameters change (for example a change in the arrival rate or in the transport mode priorization), the performance of the chosen storage policy may change, which makes it necessary to determine repeatedly the best suitable policy. Determining the application range of a specific storage policy is therefore an additional goal of a research.

3.1. Terminal simulation

The information needed to model the terminal system was gathered from an in-depth literature review and from on-field research of major Austrian hinterland terminals. Our goal was to develop a generic simulation model that can be used to reproduce any terminal configuration (Gronalt, Benna, and Posset 2006). For this purpose we implemented a configuration tool that can be used as a standardized questionnaire to obtain detailed information necessary to describe a terminal which is collected with the configuration tool and which can be grouped into three categories: equipment, layout and workload. As the modelling needs to be of great detail, the input data defined by the configurator is extensive. An elaborated description of all input parameters is given in Gronalt, Posset, and Benna (2007).

The defined parameters of the configuration are systematically transmitted to the simulation, where detailed lists of import and export containers are produced and edited. The goal of this data generation step is therefore to provide a quick procedure for generating detailed experiment data in the desired composition and quantity. This generation approach enables the computation of container, train and truck data in accordance with the parameter settings and thus in regard to the distributions and patterns as entered in the configuration. Further it takes into account the existing interdependencies within container terminal operations and especially among the properties of container and transport mode. For example, while allocating a specific container to a pick-up truck, container attributes and especially storage time have to be matched with the arrival time of the truck.

The standard terminal processes were then complemented by different terminal policies and all relevant activities were modelled in detail. The model was implemented in a discrete event simulation environment and includes different objects representing train, trucks, containers, equipment and storage blocks. All these objects interact by mean of predefined dynamic rules. These dynamic rules are defined as feasibility constraint, availability constraint and priority based selection rules. The feasibility rule outlines that the allocation of equipment or storage space has to be consistent with the defined layout and access possibilities for the equipment. Some combination of yard blocks and tracks or equipment may be forbidden and have to be therefore excluded in the planning phase. The availability constraint ensures that when the equipment is requested it has to be idle, which means that it is not busy, reserved or that it is not failed. Finally the priority rules ensure the constant flow of containers in the terminal as export containers a granted a higher priority than import containers. Further the service level of trucks, measured by their dwell time in the terminal, tends to be more critical and therefore trucks are served with higher priority.

For the different storage policies (as described above) we implemented different procedures. Due to the manageable size- in terms of space and throughput- of most hinterland terminals, optimization techniques are rarely used in daily operations. Instead, work is mostly done intuitively, based on decisions defined upon individual experience. To reflect the human factor of the decision process, decision rules had to be formulated. This was an important step in order to formalize the differences between existing storage policies.

The developed simulation can be used to analyse the behaviour and to evaluate the performance of different terminal configurations. By varying model parameters, the simulation can also be used to collect a large data set which can be used to train the neural network.

3.2. Approximation of target function

The target function describes the link between terminal parameters and terminal performance. To define which parameters are relevant, a set of parameter varying replications were simulated and according to the results of the scenario-analyses a sub set of parameters was chosen. Whereas the original set, defined by the configuration data counts for more than 200 parameters (see Gronalt, Posset, and Benna 2007), the final sub set was reduced to a total of 20 parameters. These parameters can be categorized into 3 groups according to the listing in table 1. The terminal configuration parameters describe mainly the existing capacities (shifting capacity per hour and equipment type and storage capacity in TEU) and the layout of the storage block within the terminal (average transport distance for the handling equipment). The terminal workload had to be considered more deeply. The defined parameters are here the average arrival rate per hour, the fluctuation level as a percent of the arrival rate, the container length mix, the average dwell time for storage and transshipment containers and the ratio of non-stackable containers. Finally the operation strategy parameters were defined by the available terminal operation time per day, the type of rail traffic (block train, shuttle or wagon load), average available time slot for loading and unloading of trains and truck processing type (on predefined pick-up position or variable pick-up position).

To quantify the impact of a parameter variation on the terminal performance, a set of performance indicators was defined. The chosen performance indicators can be grouped into 2 categories: throughput and service quality. Examples for throughput indicators are total number of moved load units and average number of served transport modes per time unit. Examples of service quality indicators are average remaining time in the system for each transport mode and ratio of unproductive moves.

Parameters and performance indicators define the input vector v of the neural network.

Estimating the target function is finally done by developing a radial-basis-function (rbf) neural network (Funahashi 1989), which is a special type of a two-layered Neural Network and which is particularly flexible in estimating non-linear functions. A rbf-neural networks is defined by its input neurons, one hidden layer and output neurons. Each processing unit or hidden unit of the hidden layer implement a radial activated function.

By simulating a wide range of terminal configurations and collecting the herewith generated performance indicators, the weights of the radial-basis-function can be found. The resulting data set contains the information relating configuration parameters to terminal performance and can therefore be used as a training set for the neural network, to estimate the function of terminal performance in relation to the input parameters.

3.3. Terminal optimization

Once the target function is estimated, it is integrated into a second simulation, which closely interacts with the neural network. This hybrid simulation is comparable to the first generic simulation and only differs in terms of terminal policies. In the first simulation, terminal policies are defined as simulation input at the beginning of each replication and cannot vary during the simulation run. In the second simulation (integrating the neural network), an initial policy is determined according to the target function at the beginning of the replication which can be changed afterwards if necessary. This is done with respect to changes occurring in the system, mainly due to variations in the workload. In fact, parameters are continuously monitored and sent repeatedly to the neural network which triggers a new policy when a favourable terminal performance can be expected.

The optimization problem is therefore to minimize the number of unproductive moves and to minimize the handling time per container. This is done by adjusting the storage policy in accordance with changes in terminal configuration and workload.

As a result, the integrated simulation dynamically optimizes terminal operation and alerts terminal and yard manager when a change in terminal status is occurring.

4. CONCLUSIONS

In this paper we show that the combination of simulation and neural networks techniques can be used to develop an optimization tool for hinterland terminals. Due to the complexity of terminal operations and the great number of existing parameters and interdependencies, an extensive analysis of all links relating terminal configuration and terminal performance is not possible. The explicit formulation of a non-linear function can therefore be resolved by using a neural network approximation. Especially for terminals with no decision support systems, this can be used to underline strategic decisions with regard to investments in information management systems supported by OR-techniques. In fact, terminal managers are often interested in investigated the marginal efficiency of terminal operations, which can be shown by assigning the best operating policies for a specific terminal setting.

As we describe in this paper, we concentrated on one area of the terminal, which is the storage area. In order to model all terminal processes, we still need to integrate further optimization areas. A starting point would be to consider the optimization problem which occurs when allocating and scheduling the handling equipment. For this purpose we need to develop a second neural network to estimate the relation between equipment allocation and scheduling and terminal performance. Finally the interaction of the two neural networks has to be considered.

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