PREDICTION OF ARRIVAL TIMES AND HUMAN RESOURCES ALLOCATION FOR CONTAINER TERMINAL

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ABSTRACT

The purpose of the work described in this paper is to construct and implement prediction models for optimizing container handling in particular at Cagliari's Terminal Container.
Prediction models are based on heuristic algorithms such as neural networks and classification and regression trees and evolutionary algorithms such as Genetic Algorithms (GA) and Ant Colony Optimization (ACO). These models form part of a Web Oriented Decision Support System, for real time external data acquisition (GPS information, weather information, etc.), providing operators with the information processed in real time.
The most commonly used parameter for assessing terminal performance is productivity, namely the number of containers handled in the unit of time considered.
This parameter can be associated with the terminal as a whole, or with the ship, the stevedores, each vehicle used, the single operator and related to different time intervals (year, month, week, day, hour and shift). Usually the hourly average is considered for monitoring operations and identifying shortcomings.
The rate at which operations are performed can significantly reduce turn round time and thus minimize the loss of productivity associated with the ship's time in port.
Because of the complexity of analyzing decision-making processes two sublevels are defined, that differ for type of decision and time horizon:

- The first level, generally organized around a weekly time horizon (from 10 to 1 days prior to ship's arrival in port), for scheduling operations and activities in the different areas such as, ship, quay, yard, for making decisions that satisfy the different requirements;

- The second level, aimed at specific resource allocation (personnel and equipment) on the basis of the decisions made at the first planning level in order to maximise productivity and minimize costs over a time horizon of roughly 24h.

Both levels of planning are characterized by temporal fragmentation and uncertain information. The information is received at undefined times and is continually updated, resulting in uncertain content. The strong dependence of the planning process on information flow, means it is necessarily dynamic and makes it difficult to effectively optimize and integrate decisions over sufficiently broad time horizons.
The aim of the study is to construct a model for predicting containership arrivals using heuristic-based evolutionary algorithms. The so-called “Inspect Inspired Algorithms” are proving effective tools for solving industrial optimization issues.
In this study the different models proposed are implemented in a “Decision Support System”, while data are analysed from a temporal aspect adopting a “learning from data” approach. Indeed the observation of real data (actual arrival time of ships and handling in port) form the knowledge base which relies on learning from the past. All discrepancies observed between prediction models and reality, along with other factors governing that condition prediction errors, create a historical base on which models are automatically recalibrated.
This approach has the dual purpose of analysing the causes (shortcomings) of prediction errors while refining models for future prediction; an analysis of the causes and effects of recalibrating the models.
The proposed DSS can also be used for simulation purposes. In fact the algorithms will be implemented for studying the effects of external variables taken individually or interacting with one another, thus providing a useful planning tool.
Keywords: optimizing container handling, containership arrivals prediction, Decision Support System.

INTRODUCTION

A seaport terminal is a complex system within which a broad variety of operations is carried out involving a wide array of resources that need to interact in a 24 hour operating cycle. The terminal operator aims to maximize efficiency, i.e. achieve the largest number of movements at the least possible cost.
The operations carried out in a terminal are characterized by a large number of variables and constraints that increase their complexity. Several factors, not always easy to control, can affect the quality of services provided and overall efficiency.
Demand uncertainty further complicates the task of planners and as a result, the effectiveness of planning itself. To be able to predict the delay of ships, operators need to know the actual time of arrival in port so as to be able to determine more accurately the demand for each work shift. In this way the resources required for meeting that demand can be allocated with greater certainty, avoiding under or overmanning at the planning stage.
This is a major issue in a port system where the cost of manpower is relatively high. The efficiency of a seaport terminal cannot therefore be divorced from optimizing human resources management, an essential factor especially in systems having a low level of automation. Human resources management is a very complex issue, terminals have to be

manned 24 hours a day, considering that numerous workers interact with each other and that the operations are intrinsically random.

Additionally, because the different operations carried out in terminals are strong interrelated, there is a need not only to maximize efficiency, but also to ensure proper coordination, hence to solve integrated decision-making problems. However, the decision making processes involved in terminal operations can sometimes be so complex that they become unmanageable without the support of suitable methodological tools.

The work presented here forms part of a broader research project aimed at developing a Decision Support System (DSS), comprising different but strongly interconnected modules, designed to assist terminal planning.

The DSS incorporates four modules:

- Forecasting module
- Optimal human resources allocation module
- Optimal equipment allocation module
- Maintenance module

This paper describes the studies conducted to date for the first two modules. Using forecasting algorithms, the first module provides an answer to the problem of demand uncertainty. The second module, on the other hand, uses output from the first module as input data for determining optimal manpower allocation.

Though traditional statistical tools are currently used as planning support, day to day management of terminal operations still relies heavily on planner experience. Therefore tools need to be devised that provide planners with objective and analytical answers. Of the most effective tools available for accurate forecasting we opted for a dynamic learning model based on neural networks, able to solve information uncertainty on inbound flows. The main reasons for choosing this type of model lie in the irregular time series for ship delays and the complexity of the phenomenon being studied.

On the other hand, the complexity of daily resources planning requires tools that take variables and constraints into account and deliver the best solution without upsetting the planning arrangements at a higher level.

As can be seen, a tool is required that is capable of preventive activity planning and rapid rescheduling in the event of disruptions caused by unforeseen events. In the light of these considerations, an optimizing approach of the resources allocation type appears to be the most suitable as, among other things, it also matches the requirements for efficiency and non intrusiveness.

The use of an integrated tool such as DSS, ensures fast and flexible planning of terminal operations, while achieving a substantial reduction in costs, greater efficiency and as a result enhanced terminal competitiveness.

STATE OF THE ART

State of the art: Forecasting module

Demand uncertainty plays a decisive role in terminal organization. Attempts have been made to develop an innovative a model for short term forecasting, the most crucial time period in that it concerns updated information for resources optimisation.

On a daily basis, there remains the uncertainty of ships' arrival time in port. Knowing the extent of this delay is essential for planning at least over a 24 hour period. Several approaches can be adopted to address this problem. Comparison of traditional statistical methods with neural networks used for predictive purposes conducted in 1998 (Zhang, 1998) showed that neural networks perform better when major irregularities are present, for discontinuous time series and for short time series. Further, their flexibility, non linearity and arbitrary function mapping makes neural networks useful predictive tools.

Celik (2004) uses a neural network for modelling freight traffic distribution over short time horizons. The results were an improvement over those obtained using a gravity model developed by the same author.

The work that most closely matches the application concerned with here was published by Bilegan et al. (2006) and aimed to predict the number and type of railway wagons required daily at the land interface of an intermodal container terminal in Canada. Again promising results were obtained with a neural network model, specified using an iterative trial-and-error procedure with the aid of javaNNS software.

Carbonneau (2007) conducted a comparative analysis of dynamic learning (neural networks, recurrent neural networks, support vector machines) and traditional methods (naïve forecasting, trend, moving average, multiple linear regression and time series models) applied to logistics. The findings showed that neural networks outperformed the other techniques.

On the other hand, two main limitations for neural networks are reported in the literature. First of all, no definite methodology exists for correctly specifying the model, which explains why the iterative trial-and-error procedure is more frequently used, and secondly the result obtained is strongly data-dependent and dependent on model specification.

Closer examination of the literature on NN model specification, revealed that the major focus is on choice of input variables as this influences network topology and, as a result, computational properties, generalization ability and above all, prediction efficiency. For this reason, in the present study attention has also been focused on data pre-processing.

The methods used for choosing the input variables are classified in the literature into two road-groups:

- model-free methods: whereby using chiefly statistical techniques, it is possible to select/reduce input variables on the basis of their significance and/or importance. This process takes place regardless of the neural network model used. (Papadonkontantakis et al. 2005, La Rocca e Perna, 2005). These models are used in the present study.

- model-based methods whereby input variables are chosen on the basis of the predictive efficiency of the neural network. Using an iterative procedure, a different set of input variables is selected for each iteration and at the end of the procedure the best performing set is chosen (Bowden et al, 2004, Li and Peng, 2006; Saxèn and Petterson, 2006).

Furthermore, Zhang (1998) points out that apart from the number of input and output nodes, the factors that most influence network performance, and hence the results obtained, are:

- Variables normalization;
- Choice of learning algorithm and related parameters;
- Choice of training and validation sets;
- Choice of number of hidden layers and nodes.

Determining the number of hidden layers and nodes requires special attention in order to avoid overfitting, which results in the loss of network generalization ability. Thus network complexity needs to be checked.

State of the art: Optimal human resources allocation module

Optimum allocation of human resources is also a major challenge in seaport terminals. Current research focuses on planning at the tactical and operational levels, developing optimization models. These models overcome the limitations of simulation models, which are impracticable when dealing with large number of alternatives, require long development and validation times and are not generalizable to other settings.
A plethora of literature exists on shift scheduling problems, proposing planning models which have however been developed for sector-specific applications and therefore differ from one to another. Some universally applicable models have also been developed (Beasley and Cao, 1998) but they perform poorly in applications requiring flexible and rapid responses as is the case of port terminals, where the number of ships to be handled in a single shift is far from certain and not known well in advance.
Essentially three approaches are proposed in the literature for addressing daily scheduling of human resources in a container terminal:

- Scheduling: an algorithm widely used in the literature, creates a work queue system for each terminal staff member in order to reduce overall delays to a minimum (Hartman, 2004). Meersmans and Wagelmans (2001) address the problem of integrated equipment scheduling for an automated terminal adopting an optimizing “beam search” approach; Park and Kim (2003) on the other hand propose a specific scheduling algorithm for the berthing plan and quayside cranes.

- Shared platforms (Dell'Olmo & Lulli, 2004); the terminal is modelled using a network of complex platforms, each having an engineered and an operating capacity. The problem consists of a kind of generalized scheduling among platforms.

- Resource Allocation: (Imai et al. 1999, Gaudioso 1999, Gambardella 2001, Legato & Monaco 2004, Cordeau et al. 2005).

The resource allocation approach appears to be the most suitable for those cases where it is required to make the best use of a limited amount of resources in order to maximize benefits. This approach has been adopted by a number of authors and appears to best match the characteristics of efficiency and non intrusiveness on the system.
Gambardella for instance, formulates a network design problem for determining, for a 24-hour time horizon, the number and type of resources required per shift to satisfy container handling demand.
Gaudioso has provided a major contribution to human resources allocation. He defines two planning levels in transhipment terminals, monthly and daily. For monthly scheduling, a sequence of work and rest shifts is prepared for each worker that is then refined at the daily level.
Legato and Monaco contributed to furthering progress in this direction. Drawing on the work of Gaudioso, they developed a model for daily human resources allocation in a transhipment terminal which forms the basis of the optimization model proposed here.

GENERAL LAYOUT OF A CONTAINER TERMINAL

Container terminals work four 6-hour shifts around the clock, every day as follows:

- 1st shift: 01:00 – 07:00

- 2nd shift: 07:00 – 13:00

- 3rd shift: 13:00 – 19:00

- 4th shift: 19:00 – 01:00

Two-level personnel scheduling is used, monthly and daily. Monthly scheduling ensures personnel is available for each working day, in conformity with shift arrangements as well as contractual obligations and labour regulations. Because of the uncertainty of demand for that period, the schedule for each day assigns “fixed” workers to one specific shift and “flexible” workers to a shift to be decided during daily scheduling, once demand has been determined with greater certainty. Contractual terms for flexible shifts specify that a flexible worker will be assigned to a shift with only 24 hours advance notice, though the monthly schedule establishes the days on which he/she will work. Once the daily schedule has been prepared only the distribution of workers across shifts can be altered, the total number of workers per shift remaining unchanged. In the event demand requires additional manpower then external workers are hired, usually employed by stevedoring companies for ground operations and

truck trailer driving. Clearly the cost of hiring external manpower is higher and should be avoided as far as possible.
Clearly both scheduling levels are characterized not only by process complexity but also by temporal fragmentation of the information and the longer the scheduling horizon, the greater the information uncertainty. Under these circumstances, the problem of predicting ships delays has negative effects on planning efficiency. Poor forecasting, combined with the possibility of unforeseen events, translate into higher costs because of the additional workload involved. The ability to predict ship delays means knowing their exact time of arrival in port so that the demand for each shift can be determined more accurately. Once this information is known then human resources can be allocated accordingly, avoiding under or overmanning.

METHODOLOGY

Methodology: Forecasting module

For predicting ships arrival at the terminal the study examined the calibration of a neural network based simulation model.
After a review of the pertinent literature, it was decided to opt for neural networks basically for two aspects associated with the phenonemon under study (Haykin 1994, Zhang, 1998, Potvin e Smith 2001), namely its complexity and the irregular time series of arrivals.
The main steps involved in model structuring are listed below:

a) Choice of predictive approach;

b) Choice of paradigm;

c) Choice of input variables;

d) Variable normalization;

e) Choice of network architecture;

f) Choice of number of hidden layers and nodes;

g) Choice of learning algorithm and related parameters;

h) Interpretation of results.

The study was initially based on a model, developed at Cagliari University, with the following characteristics:

a) A predictive causal approach was used: the network was trained to recognize relationships between a given number of appropriately chosen, independent input variables and the output variable, the ship's delay.

b) An MLP paradigm was employed (fully connected, feedforward), the most widely used in the literature. Information flow across the network is feedforward. Information propagates unilaterally moving from the units of one level to the next: output cannot be used as input.

c) Input variables were chosen using a priori knowledge without the aid of special descriptive or statistical techniques. Eight input variables were chosen: “ship name”, “ship length”, “transit time”, “number of stevedores required for unloading”, “number of stevedores required for loading”, “ETA month”, “ETA day of the week”, “ETA hour”.

d) It was necessary to normalize the variables, appropriately scaling them to the transfer function used. In this case an along-channel normalization was used: as a logistic transfer function was used the range [0,1] was chosen.

e) The 194 patterns contained in the database were divided up among the trainiing (80%) and validation sets(20%). Once the network had been trained, predictive aibility was evaluated on a different set of data, the validation set.

f) In determining the number of hidden layers and nodes, using a trial-and-error procedure, adding hidden layers was thought might slightly improve performance, but on the other hand would make the error function more complicated and require greater attention for finding the optimum weights. Additionally, based on the considerations reported by Hornik (Hornik et al., 1989), it was decided to use networks having 1 or 2 hidden layers.

g) The learning algorithm and related parameters were also determined using a trial-and-error procedure: an iterative procedure that consists in training several networks with different architecture and choosing the one that minimizes error. For equal error rates, the network with the simplest architecture was chosen.

With the aid of JavaNNS software, also used by Bilegan et al. (2006), the model that performed best was obtained with just one hidden layer and 30 nodes. The Batch-Backpropagation algorithm yields the best results defined as follows:

- Learning rate (coefficient that determines the extent of weight change) = 0.2;
- Number of learning cycles (that achieves the best compromise between accuracy and generalization) = 20,000.

h) The smallest validation error expressed in %, was 8.2%; equated to the range [-24h, +24h] this corresponds to a mean error of roughly 4 hours in delay prediction This absolute value of this result should be considered as it takes into account a prediction of 4 hours late/early, giving an uncertainty range for ship arrival in port of around 8 hours.
Though satisfactory in scientific terms, the result obtained is not yet acceptable for the specific operating context. In fact, it is easy to deduce that:

- The risk exists that the ship’s actual time of arrival covers three shifts;
- The possibility of univocally determining the demand for each shift can be completely ruled out.

These considerations form the starting point for the implementation of the new model discussed in the “Discussion: Forecasting module” section.

Methodology: Optimal human resources allocation module

The optimization model was also based on an earlier integer linear programming model for optimal allocation of drivers in a transhipment terminal, developed at the University of Cagliari.
The optimization model formulation is shown below, along with a brief description of the architecture.

OBJECTIVE FUNCTION:

MIN $\Sigma_{i=1,nt} \Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l}$ ($c_{i,k}$ - ((a_z ($prod_{i,qc}$ + $prod_{i,rt}$ + $prod_{i,ra}$) / 3) g_z) $x_{i,j,k,z}$)+
+ $\Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l}$ (b $v_{j,k,z}$) +
+ $\Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l}$ (d $u_{j,k,z}$)

SUBJECT TO

(1) $\Sigma_{i=1,nt} x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} = nm_{j,k} * r_{j,z}$	$\forall z \in Na, \forall j \in J, \forall k \in K$
(2) $\Sigma_{i=1,nt} x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} = nh_{j,k} * h_{j,z}$	$\forall z \in H, \forall j \in J, \forall k \in K$
(3) $y_{i,j} = yt_{i,j}$	$\forall i \in Tj$
(4) $\Sigma_{k=qc,rt,ra} \Sigma_{z=1,l} x_{i,j,k,z} = y_{i,j}$	$\forall i \in N, \forall j \in J$
(5) $\Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l} x_{i,j,k,z} = 1$	$\forall i \in N$
(6) $v_{j,k,z}$ >= 0 integer	$\forall j \in J, \forall k \in K, \forall z \in Z$
(7) $u_{j,k,z}$ >= 0 integer	$\forall j \in J, \forall k \in K, \forall z \in Z$

The optimization problem is treated as a least cost problem. The cost function is associated to the Boolean variable $x_{i,j,k,z}$ (equal to *1* if the worker *i* is assigned to shift *j*, task *k*, activity *z*; *0* otherwise) and is defined as:

$$(c_{i,k} - ((a_z(prod_{i,qc} + prod_{i,rt} + prod_{i,ra})/ 3)g_z)$$

In addition to the cost of permanent staff, the objective function is required to minimize the cost of any external workers, (*v* on the right hand side) and indicates personnel shortfall (*u* in third term). The problem variables are briefly described in the following table:

Table 1 - Variables of the Integer Linear Programming model for personnel allocation.

VARIABLE	TYPE	DESCRIPTION
$X_{i,j,k,z}$	Permanent staff	binary variabile: x =1 if worker i is assigned shift j, task k, activity z; 0 otherwise
$V_{j,k,z}$	External workers	number of external works required for shift j, activity z for task z=ra (truck trailer) alone
$U_{j,k,z}$	Shortfall	indicates personnel shortfall, number of workers, shift j, task k and activity z

The two criteria adopted for human resources allocation are specified within the objective function. These are labour costs and productivity, which have been treated taking into account two important aspects:

- Multiskilled workers, and hence the need to minimize additional costs ($c_{i,k}$) incurred by assigning workers to lower level tasks than their main task;

- The need to assign more experienced crews to high priority activities. More precisely, the deterministic quantity ($prod_{i,qc}$ + $prod_{i,rt}$ + $prod_{i,ra}$)/3) is introduced to provide a rough estimate of crew productivity, ($prod_{i,k}$ represents productivity time series achieved by worker i performing task k). A standard crew comprises: 1 quayside crane operator (qc), 2 yard crane operators (rtg) and 3 truck trailer drivers (ra); this combination ensures the best mix of productivity and minimum idle time. Housekeeping, which concerns handling operations inside the yard, does not require quayside cranes. In order to account for actual operating conditions, crew productivity is corrected using a a_z, a function of the operating conditions for activity z.

On the other hand, the coefficient g_z ensures that the more experienced crews are assigned to high priority activities.
Lastly the constraints for defining the set of admissible solutions are summarized in Table 2. The critical properties of the model described together with the new model formulation are discussed in the “Discussion: Optimal human resources allocation module” section.

Table 2 - Constraints of the Integer Linear Programming model for personnel allocation.

CONSTRAINT	DESCRIPTION
1	Ensure manpower demand is satisfied for the working vessel maintaining correct crew composition
2	Ensure manpower demand is satisfied for housekeeping operations maintaining correct crew composition
3	Adhere to monthly scheduling for workers with shifts already assigned
4	Account for logic connection for monthly scheduling adherence
5	Ensure that each worker is assigned only one shift, one task and one activity
6	Concerns integrity and non negativity of the variable v
7	Concerns integrity and non negativity of the variable u

DISCUSSION

Discussion: Forecasting module

The main shortcoming of the initial prediction model, as mentioned in the “Methodology: Forecasting module” section, concerned the choice of input variables, which was made without the aid of specific variable selection and reduction techniques. In an attempt to improve predictive quality, the attention was focused on data pre-processing.
Starting from the initial set of 8 variables, first of all a ninth was added using a priori knowledge, “ship’s port of departure”.
Analysis of the correlations made it possible to eliminate, using the chi-squared tests, the redundant variables, variables strongly correlated with others that do not provide any additional information on the phenomenon being studied. Using multivariate statistical techniques (multiple correspondence analysis and cluster analysis) it was possible to

analyze simultaneously the remaining variables and reorganize them, using combined simultaneous analysis of the χ^{2}[(1)] and Valor Test[(2)], depending on their significance[(3)].
The results of the significance test were then analyzed and 4 sets of alternative inputs determined (Table 3).

Table 3 - χ2 and Valor-test values for the variables in the 4 sets chosen.

	1st SET (7 variables)		2nd SET (3 variables)		3rd SET (4 variables)		4th SET (5 variables)	
Variables	χ^2	v-test	χ^2	v-test	χ^2	v-test	χ^2	v-test
Name of ship	739.9	21.1	895.1	25.4	1000.4	26.0	841.2	23.1
Departure port	449.2	18.6	352.9	16.6	463.7	18.9	406.3	17.4
No, crew loading	289.9	10.5	187.4	8.1	314.8	11.4	407.4	14.2
No. crew unloading	218.3	6.5			199.1	5.6	188.2	5.1
ETA month	219.0	7.8					226.4	8.1
ETA day of week	139.0	6.9						
ETA hour	261.54	4.77						

Considering the 4 sets of input data selected, a new neural network was specified, and its predictive ability assessed. The study comprised two separate test phases.
The first phase consisted in comparing the results obtained implementing numerous networks varying the following:

- The number of input variables using alternately the first, second, third and fourth set;
- The learning algorithm: using backpropagation, backpropagation with momentum, batch backpropagation or resilient propagation, the algorithms most widely used in the literature;
- The learning parameters: number of learning cycles, learning rate, etc.;
- The number of hidden nodes: 5, 10, 20 or 30 nodes per each hidden layer.

[(1)] χ2: test of independence of two variables. The null hypothesis is tested that two classification criteria, when applied to the same data set are independent. If the distribution with respect to one criterion is not influenced by the classification with respect to the other, then the two classification criteria are said to be independent.

[(2)] Valor Test, this represents the deviation of the significant variable with respect to a normal distribution. The principle is as follows: for a sample size of n individuals q nominal variables have been observed. A particular group of nk individuals is identified. How do we classify in order of importance the variables that best characterize that group? A variable will not characterize the group if the nk values found appear to have been drawn at random from the n values observed. The more doubtful the hypothesis of a random draw, the more significant that variable will be for characterizing the group. The valor test can thus be written:

$$V..T. = \frac{n_{jk} - n_k \times \frac{n_j}{n}}{\sqrt{n_k \times \frac{n-n_k}{n-1} \times \frac{n_j}{n} \times \left(1 - \frac{n_j}{n}\right)}}$$

If v-test > 2, the mean of the group will differ significantly from the sample. Thus the higher the v-test, the more significant and characterizing the variable will be for that group.

[(3)] Statistical analyses were performed with the aid of the French SPAD.N software (Système Portable Pour l’Analyse des Données).

All the networks implemented in this phase had just one hidden layer.
Table 4 shows the minimum prediction errors, expressed in %, for the screening(4).

Table 4 - Minimum errors, expressed in %, for the first test phaset.

		Learning cycles: 40,000							
	Algorithm	**Backpropagation**		**Backpropagation with momentum**		**Batch backpropagation**		**Resilient propagation**	
	Hidden Nodes	**dmax=0.1**		**dmax=0.1**		**dmax=0.1**		**dmax=0.1**	
		h=0.1	h=0.2	h=0.1	h=0.2	h=0.1	h=0.2	d=0,1 d=50 a=4,0	d =0 d=30 a=2,0
1st set: 7 var	5	12.12	14.83	13.42	13.78	9.33	9.36	14.14	10.25
	10	21.45	113.84	16.12	17.89	9.64	9.75	18.17	10.25
	20	16.73	18.57	17.89	21.91	9.38	9.80	18.14	10.25
	30	19.75	19.24	22.14	25.69	8.89	9.38	24.23	10.25
2nd set: 3 var	5	7.75	8.37	8.48	9.06	5.95	5.99	10.05	6.16
	10	8.43	8.83	8.53	8.94	5.55	5.85	10.49	6.16
	20	8.66	8.49	8.57	8.72	5.66	6.32	10.49	6.16
	30	8.19	8.77	8.79	9.02	5.83	6.32	10.49	6.16
3rd set: 4 var	5	11.83	12.25	13.15	18.11	9.21	9.21	-	-
	10	13.67	14.87	13.08	17.32	9.03	9.44	13.49	10.49
	20	13.86	15.10	13.42	16.40	9.46	9.38	12.96	10.44
	30	-	-	-	-	-	-	-	-
4th set: 5 var	5	12.00	-	13.78	-	9.00	-	12.25	-
	10	13.71	-	14.14	-	9.27	-	13.42	-
	20	14.83	-	18.97	-	8.83	-	12.45	-
	30	-	-	-	-		-	-	-

An important result already emerged in the first screening for the chosen set of variables. The best networks had 3 variables in the input level. Table 5 shows the substantial reduction in minimum prediction error, from 9.3% (7 variables) to 6% (3 variables).

Table 5 - Minimum prediction error during learning for the 4 sets of variables chosen.

	1st SET (7 variables)	**2nd SET (3 variables)**	**3rd SET (4 variables)**	**4th SET (5 variables)**
Error	**9.3%**	**6%**	**9%**	**8.8%**

It is important to note that in choosing the best model, we considered not only the error values but also the training error and validation error curves obtained during learning.
Considering the sets with 4, 5 and 7 input variables, we found that in practically all the tests, these curves exhibited two different trends during training:

(4) The percentage error is calculated as (√MSE)*100, where MSE=mean square error.

- Practically constant for both: this can be explained by the fact that the additon of less significant variables to the set with 3 variables, might constitute an impediment in the learning process: the network "does not learn" (Fig. 1a);

- The training error curve slopes downwards while the validation error curve slopes practically upwards (irregularly) and in some cases even intersects and surpasses the training error curve. In the latter case, overfitting has occurred, a problem associated largely with network architecture design: the network loses generalization ability (Fig. 1b).

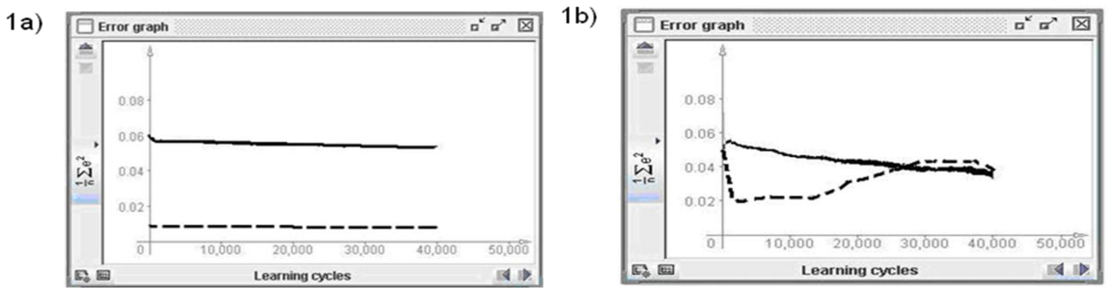

Figure 1 - Trend of training error (continuous) and validation error (dashed) curves during training.

On the basis of these results, in the second test phase a new specification was developed keeping the number of input variables (3) and learning algorithm (batch-backpropagation) unchanged and attempting to improve the network architecture by varying:

- The number of hidden layers: 1, 2;

- The number of hidden nodes: 5, 10, 20 e 30 for just one hidden layer
  4+4 (8), 5+5 (10), 6+6 (12) and 7+7 (14) for two hidden layers;

- Learning parameters.

Table 6 shows the results for the second test phase (minimum error expressed in %).

Table 6 - Minimum error expressed in %, for the second test phase.

	LEARNING PARAMETERS							
	h = 0.25		**h = 0.20**		**h = 0.15**		**h = 0.1**	
Hidden Nodes	**dmax0.05**	**dmax0.1**	**dmax0.05**	**dmax0.1**	**dmax0.05**	**dmax0.1**	**dmax0.05**	**dmax0.1**
8	5.91	5.65	5.65	5.38	6.08	5.83	5.65	5.65
10	6	5.65	5.47	5.91	5.83	5.38	5.91	5.47
15	5.47	5.83	5.65	5.83	6.16	5.83	5.74	5.47
4+4	6.16	**5.47**	5.74	5.47	5.83	5.91	9.7	9.64
5+5	5.83	6	6.16	5.74	6.16	5.74	6.24	5.65
6+6	-	-	5.91	6	-	5.91	5.47	5.74
7+7	-	-	-	-	-	-	6.16	5.83

Over 120 models were implemented in the first and second phases with the aid of JavaNNS software. The best results were obtained for the following model:

- Size of learning set: 158 patterns;
- Size of validation set: 39 patterns;
- Paradigm: feedforward multi layer perceptron fully connected;
- Input nodes: 3;
- Hidden layers: 2;
- Hidden nodes: 4+4;
- Output node: 1;
- Learning algorithm: BatchBackpropagation;
- Learning rate: 0.25;
- Learning cycles: 40,000.

The analysis conducted with the neural network yielded positive results. It was possible to reduce validation error by almost 34%, from 8.2% to 5.47%, as shown in Table 6.Mean delay prediction error decreased from 4 h to around 2 h 40 min (absolute value), obtaining an uncertainty range of less than 6 hours (5.20h).
Two basic considerations emerge from this analysis:

- The possibility that the ship's predicted arrival time spans 3 shifts (most critical condition) is eliminated;

- The possibility exists, first ruled out, that the predicted arrival time falls within a single shift, enabling to determine univocally the demand for that shift.

So in practice, the certainty exists that personnel can be scheduled for two shifts instead of three.

Discussion: Optimal human resources allocation module

A number of personnel allocation tests were carried with the optimization model, described in the "Methodology: Optimal human resources allocation module" section, assuming demand falls short of, is equal to or exceeds manpower resources. For demand shortfall constraint 5 had to be modified to include the possibility of worker "i" not being assigned a shift.
Analysis of the structure identified two aspects that leave room for improving the formulation and obtaining a more realistic level:

a) Interperiodicity;

b) Productivity.

a) Interperiodicity; the model described is static. The demand refers to a single shift so one needs to determine the number and composition of the crews for satisfying that demand, assuming a given manpower availability for meeting the needs of the different shifts. Should insufficient personnel be allocated to handle the workload then the model indicates the shortfall per shift and per task, resorting to "fictitious" workers: the $u_{j,k,z}$. This type of solution does not however realistically reflect the operational situation in seaport terminals where, by contrast, any tasks left undone at the end of a shift, are passed on to the next one. Thus workers starting the next shift not only have to meet the demand envisaged for that shift but also complete any work left undone in the previous one.
Thus a dynamic model is required, in other words that envisages work undone in one shift due to insufficient manning being passed on to the next, considering the interperiodicity over the shifts and over the 24 hours.
In the static model the constraint for satisfying demand is posed in terms of demand balance: $X_j + V_j + U_j =$ *period demand j*.
When $X_j + V_j <$ *period demand j,* part of the demand predicted for that shift cannot be satisfied because of undermanning. This shortfall is indicated by the non null value taken by the variables "$u_{j,k,z}$". In the cost budget these "fictitious" workers, that actually represent undermanning for the work period, will necessarily result in much higher costs compared to actual workers, be they permanent staff or external workers.
The variabile of interperiodic nature will therefore representing undermanning of a shift, which equates to demand not being satisfied in that shift.
Bearing in mind the above considerations, the dynamicity constraint of demand on shifts can be formulated as follows:

For cargo handling:

a) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} - \mathbf{u_{j-1,k,z}} = nm_{j,k} * r_{j,z}$ $\quad \forall z \in Na,\ \forall j \in J,\ \forall k \in K,$ **with j≠1**

b) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} = nm_{j,k} * r_{j,z}$ $\quad \forall z \in Na,\ \forall j \in J,\ \forall k \in K,$ **with j=1**

For housekeeping:

c) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z}$ **$- u_{j-1,k,z}$** $= nh_{j,k} * h_{j,z}$ $\forall z \in H, \forall j \in J, \forall k \in K,$ **with j≠1**

d) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} = nh_{j,k} * h_{j,z}$ $\forall z \in H, \forall j \in J, \forall k \in K,$ **with j=1**

With the new system of constraints work left undone in shift j is automatically added to the workload for shift j+1 overcoming the staticity of the previous formulation.
The undermanning detected in the 4th shift will on the other hand increase the workload predicted for the first shift (j=1) on the next day.
The uncompleted work predicted by the model for the last shift of the previous day, is a known value (though it does suffer from some degree of uncertainty) and the planner will input this, directly into the database, thereby increasing the demand predicted for the first shift of the day for which personnel is yet to be scheduled; the constraint for the shift j=1 therefore remains unchanged with respect to the original formulation.

b) Productivity. The deterministic description included in the crew productivity model is unnatural. Studies reported in the literature show the productivity parameter to be influenced by numerous factors, only some of which can be controlled by the planner, and is ill-suited to being interpreted deterministically. It is important to identify those aspects influencing operations efficiency in one way or another to enable the planner to introduce the most suitable boundary conditions directly into the model.
The shift in particular has a major influence on operator fatigue and performance. This effect can be incorporated into the objective function using a new parameter "*e*", a function of the shift j. The value it takes, calibrated using statistical procedures or determined by the planner, will be input into the data files. In this way, the planner is able to optimise productivity using more detailed data, ensuring a greater degree of adherence. The model does not provide a definitive invariant indicator, but a general and generalizable tool that planners can utilize according to experience.
Based on the above considerations, the new model can be defined as follows:

MIN $\Sigma_{i=1,nt} \Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l} \, (c_{i,k} - (e_j \, (a_z \, (prod_{i,qc} + prod_{i,rt} + prod_{i,ra}) / 3) \, g_z) \, x_{i,j,k,z}) +$
$+ \Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l} \, (b \, v_{j,k,z}) +$
$+ \Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l} \, (d \, u_{j,k,z})$

SUBJECT TO

a) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z}$ **$- u_{j-1,k,z}$** $= nm_{j,k} * r_{j,z}$ $\forall z \in Na, \forall j \in J, \forall k \in K,$ **with j≠1**

b) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} = nm_{j,k} * r_{j,z}$ $\forall z \in Na, \forall j \in J, \forall k \in K,$ **with j=1**

c) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z}$ **$- u_{j-1,k,z}$** $= nh_{j,k} * h_{j,z}$ $\forall z \in H, \forall j \in J, \forall k \in K,$ **with j≠1**

d) $\Sigma_{i=1,nt}\, x_{i,j,k,z} + u_{j,k,z} + v_{j,k,z} = nh_{j,k} * h_{j,z}$ $\forall z \in H, \forall j \in J, \forall k \in K,$ **with j=1**

e) $\Sigma_{k=qc,rt,ra} \Sigma_{z=1,l}\, x_{i,j,k,z} = y_{i,j}$ $\forall i \in N, \forall j \in J$

f) $\Sigma_{j=1,4} \Sigma_{k=qc,rt,ra} \Sigma_{z=1,l}\, x_{i,j,k,z} \leq 1$ $\forall i \in N$

g) $v_{j,k,z} >= 0$ integer $\forall j \in J, \forall k \in K, \forall z \in Z$

h) $u_{j,k,z} >= 0$ integer $\forall j \in J, \forall k \in K, \forall z \in Z$

As can be observed, the constraint $y_{i,j} = yt_{i,j}$, has been relaxed as it was superfluous. There is no sense in getting the model to do something already determined in the data files.
The integer linear programming problem was formulated and solved with open source GLPK software using the GLPSOL solver, included in the GLPK package.
The model was tested for three typical situations likely to arise in terminal management:

1. Demand = Supply (Fig. 2)

2. Demand < Supply (Fig. 3)

3. Demand > Supply (Fig. 4)

Using the above software it was possible to determine, in an absurdly short time (less than 1''), optimal personnel allocation while observing the constraints and the ability of the model to realistically represent terminal operating characteristics.
Tests conducted assuming demand equal to or less than manpower supply for the period (situations 1 and 2) correctly reproduce the same result obtained with the original formulation. In fact, as there is no undermanning, the dynamic constraints do not come into play and the dynamic formulation coincides with the original static one (Figures 1a-1b, 2a-2b).
However, the same cannot be said for the third situation. In this case the original and new models yield different results (Fig. 3a-3b). The assumption that demand exceeds manpower supply in the period necessitates assigning the "u", thereby activating the dynamic constraints for moving the unsatisfied demand from one shift to another (Fig. 3a). The new model yields a more realistic representation of actual operating characteristics in a seaport terminal. This is confirmed by the higher value taken by the objective function, indicating the additional costs incurred by the terminal due to undermanning.
Further tests conducted introducing the shift parameter into the dynamic formulation but using the same data as for situation 3, yielded variations in the value of the objective function (5581.46) and in the assignment of "flexible" permanent staff. This was to be expected insomuch as the parameter "e", by changing the historical productivity data, makes it more convenient to assign to the worker one turn rather than another.

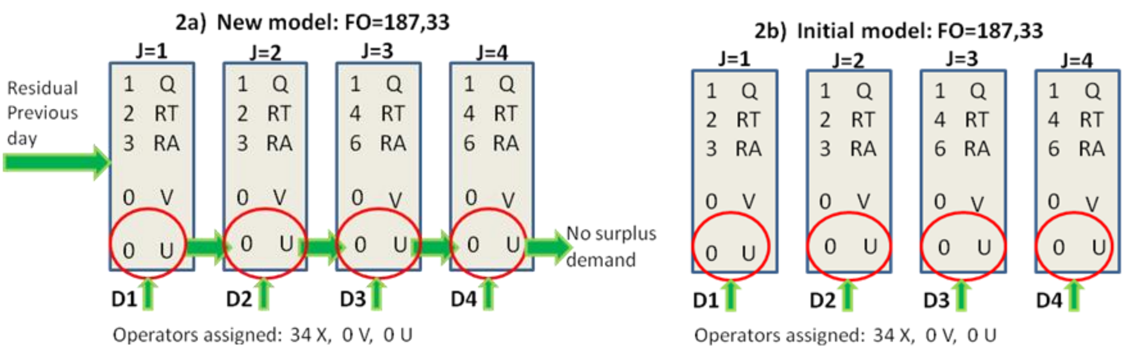

Figure 2 – Result of allocation for situation 1: Demand = Supply;
(Assumption: Demand = 4 loading/unloading gangs + 2 housekeeping gangs; Supply = 34 dockers)

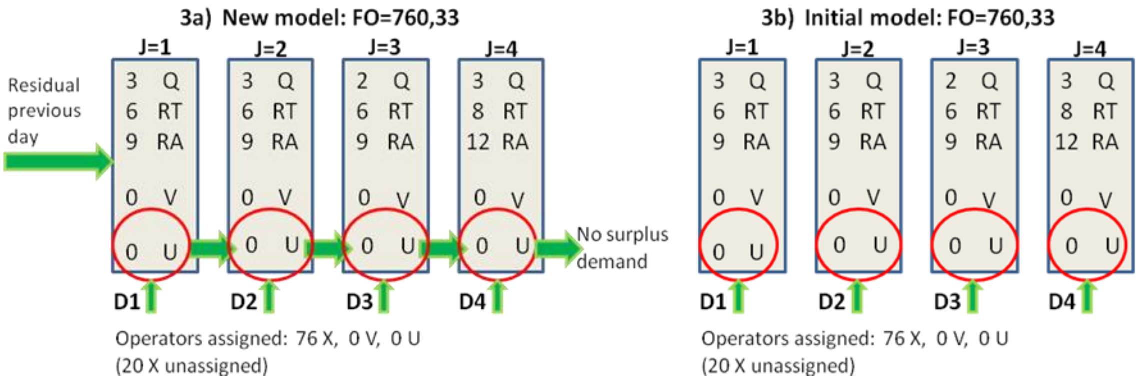

Figure 3 – Result of allocation for situation 2: Demand < Supply;
(Assumption: Demand = 11 loading/unloading gangs + 2 housekeeping gangs; Supply = 96 dockers)

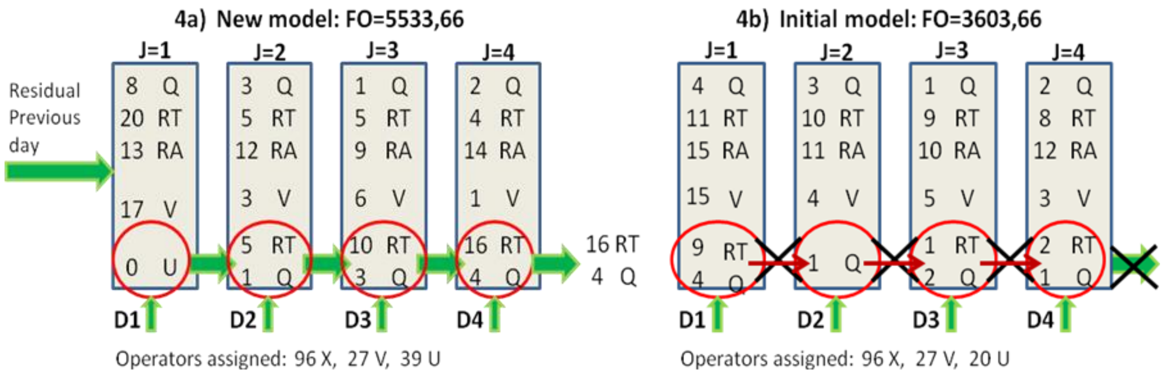

Figure 4 – Result of allocation for situation 3: Demand > Supply;
(Assumption: Demand = 18 loading/unloading gangs + 7 housekeeping gangs; Supply = 96 dockers)

CONCLUSION

The difficulties inherent in managing port operations, due to the uncertainty of demand and to the complexity of planning processes, means that planners need to be assisted at each stage by tools that support the decision making process.
This paper describes two models that support the planner in the different planning activities: a forecasting model and an optimization model.
With the neural network based forecasting model proposed here, it was possible to reduce the uncertainty interval of ships' arrival time in port, thereby increasing the accuracy of demand forecasting, with the certainty, in practice, of being able to plan resources around just two work shifts instead of three. The demand thus calculated was used as input for the subsequent optimization model. The optimization formulation is of an interperiodic nature and represents the operations actually carried out in a terminal more realistically. With this model it was possible to optimize worker allocation over the 24-hour period, taking into account actual operational requirements.
Considering the promising results achieved, the two models, appropriately revisited and integrated, can provide a useful planning support tool. This part of the research falls within a broader project aimed at developing a complete DSS capable of providing 360° support to

planners. This will reduce terminal operating costs while maximizing efficiency thereby enhancing competitiveness.

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