DEVELOPMENT OF A TERMINAL OPERABILITY FORECASTING SYSTEM: ANALYSIS OF THE EFFECTS THAT WIND GENERATES OVER VESSEL PERFORMANCE

Rebeca Gómez[1] and Rafael Molina[1,2] and Alberto Camarero[2] and Francisco de los Santos[3]

Terminals rely on optimization tools used on merchandise location, quay occupation or vehicle trajectories, in order to minimize the movements together with the time dedicated to every task. However, operations are developed into an environment that induces variability to the theoretical model used to schedule and control the operations. Given the complexity of the port operations, the artificial intelligence systems are positioned as a good choice to analyze such processes. In the near future terminals, where automation is set out as an extended reality, monitoring of operational variables carried out offers great possibilities to make a qualitative improvement in the operations management and planning models. In this work we propose a methodology to obtain operational parameter forecasts in container terminals. Moreover, a case study is developed, where forecasts of vessel performance are obtained. This way, the management strategies would be supported by an expert system, grounded on the historical data series of quay operations, and on the climatic conditions observed, as well as on the ordinary and extraordinary events that had happened in the past, from which the system is able to "learn". This work has been entirely been based on real data from a semi-automated container terminal from Spain.

Keywords: Forecasting; Container Terminals; Productivity; Operations Research; Container Data

INTRODUCTION

The set of tools that give service to the terminals for the management and planning of operations in the short term are focused on integrating the information provided by the different actors involved in the cargo transportation, so as the space availability, equipment and workforce at the terminal itself. Operations are developed into an environment that induces variability to the theoretical model used to plan and control the operations. The sources of operational disruptions, and thus, of uncertainty on the operations may be classified in 5 groups: environmental, mechanical failures, the human factor (that is able to fully paralyze the activities), the electrical supply and telecommunications, and the operations that coexist with the one that is being studied. Moreover, merely operational factors are the most likely source of uncertainty: the arrival times and the duration of the operations are estimated values yet not exact. In the other hand, modifications on the cargo manifest affect drastically to the planning. The characterization of this randomness need of detailed studies on the causes, the involved factors so as the consequences that all this generates on the management, economy and external perception of the terminal. To this, it is indispensable to have precise and complete information available on the variables that participate on the processes. Given the complexity of the port operations, the artificial intelligence systems are positioned as a good choice to analyze such processes. Neural networks in particular are characterized because of their capacity of establishing non-linear relationships (and consequently, non intuitive ones) among the variables which interaction leads to a particular operational response.

In the near future terminals, where automation is set out as an extended reality, monitoring of operational variables carried out offers great possibilities to make a qualitative improvement in the operations management and planning models. The availability of a large amount of samples of the variables that influence the performance of the operations is necessary to apply this methodology. In this context, planners' role (and that of the rest of the team) is key. These tools may not be developed without the support of the knowledge and experience of the ones that are going to be given a service. The system is conceived to ease the scheduling and planning tasks, and to make them more precise and more reliable, with consequent advantages to the business. In this work we propose a methodology to obtain operational parameter forecasts in container terminals. Moreover, a case study is developed, where forecasts of vessel's performance are obtained. This way, the management strategies would be supported by an expert system, grounded on the historical data series of quay operations, and on the climatic conditions observed, as well as on the ordinary and extraordinary events that had happened in the past, from which the system is able to "learn". This work has been entirely been based on real data from a semi-automated container terminal from Spain.

---

[1] Harbor Research Laboratory. Technical University of Madrid. C/ Profesor Aranguren s/n. 28040, Madrid, Spain
[2] Civil Engineering-Transports Department. Technical University of Madrid. C/ Profesor Aranguren s/n. 28040, Madrid, Spain
[3] Port Authority of Algeciras Bay. Avenida de la Hispanidad, 2. 11207, Algeciras (Cádiz), Spain

FORECASTING IN CONTAINER TERMINAL OPERATIONS

Neural networks have been successfully used for low-level cognitive tasks such as speech recognition and character recognition. Also they have been explored for decision support and knowledge induction. Forecasting the behavior of complex systems has also been a broad application domain for them (Adya & Collopy, 1998). Some applications include electric load forecasting, economic forecasting or forecasting natural and physical phenomena. More recently, some predictions models for container traffic (Fancello et al., 2010; Gosasang et al., 2010), freight traffic distribution (Celik, 2004), number and type of railway wagons required (Bilegan et al., 2006), throughput capacity (Yan et al., 2012) or hinterland optimization have been presented. Comparisons between traditional and modern methods have been conducted firstly by Zhang et al. (1998) and later by Carbonneau et al. (2007). For identifying guidelines that could be helpful in evaluating the effectiveness of both validation and implementation of a neural network the reader may see Adya & Collopy (1998).

METHODOLOGICAL FRAMEWORK

Systems that control operations in automated or semi-automated facilities collect data that can be used by terminal management to generate planning strategies better adapted to the historical experience gathered on the past. Until recently, it was difficult to obtain data on operational parameters, but now a huge number of parameters are continuously monitored. These data remain under exploited, however, and in this work we propose a way in which they could be put to good use.

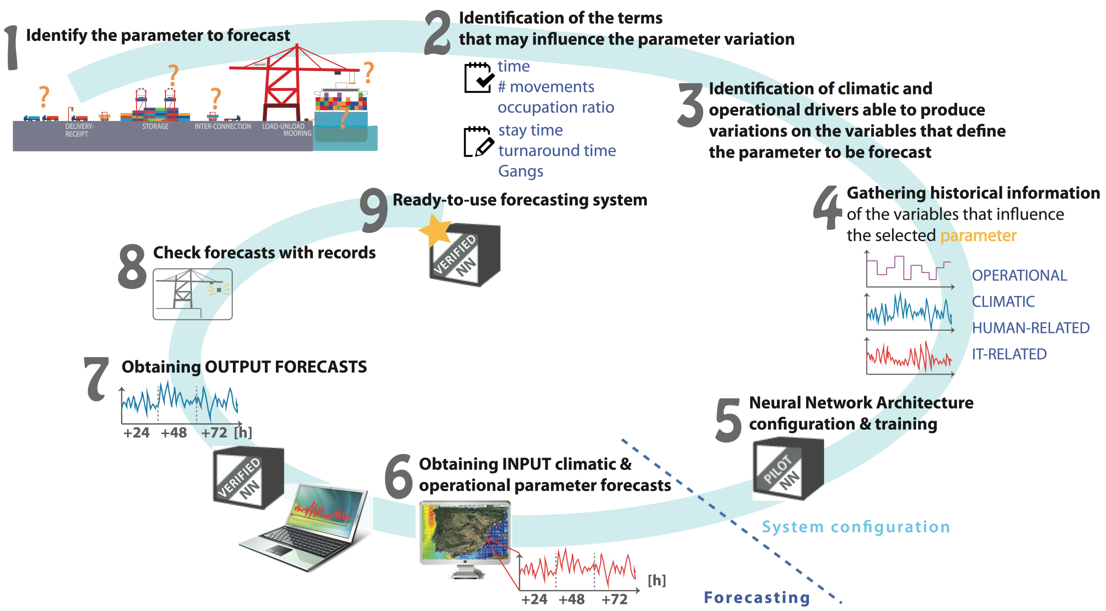

Figure 1: Process to obtain operational parameter forecasts based on historical climate and operational information

The methodology proposed comprises 9 steps that are summarized below. We will support the explanations of the methodology with examples related to the loading-unloading operation, as an introduction to the topic we will be tackling later on.

1. **Selection of the parameter to forecast**: In order to ascertain if an activity is being successfully carried out, performance parameters may be used, but others may also be selected.
2. **Identification of the terms that may influence the parameter**: The value that a parameter adopts is influenced by a number of variables, such as time, number of units, number of shifts, number of workers or the number of cranes. This is a pre-selection of the variables that will be finally used in the neural system. Later, some variables may be discarded since the system will determine that they do not play an important role in the variation of the target parameter. However, a proper identification of variables at this point will make the convergence towards an optimum solution faster. Because of this, the expert judgment plays an important role in the implementation of this methodology in a real system.
3. **Identification of climatic and operational drivers able to produce variations on the variables that define the parameter to be forecast**: Once the key variables are identified, one must

ascertain which phenomena are able to produce variations in each of them. The aim is to determine whether an Operational Limit State (OLS) will occur, which is the most limit situation that could affect the operation's performance since it will adopt a value of 0. There is no general consensus on how to identify modes of operation, although safety- or service quality-related criteria are typically applied. For example, in the case of wind, lifting operations of quay cranes stop when wind speeds make it difficult and/or dangerous to continue; while in the case of agitation in the docking area, operations are affected as the movements and accelerations of the moored ship also increase.

4. **Gathering historical data on the climatic and operational drivers**: It should be underlined that the existence of a driver is a necessary but not a sufficient condition for a stoppage to occur. Rather, a stoppage is a consequence of the combination of climatic and operational drivers that have reached certain values that together make it impossible to continue with the regular level of activity. Regarding operational parameters, the ones that are typically used in terminal management include traffic properties, ship characteristics, loading-unloading operation information, workers-related information and incidents.
5. **Creating the architecture of the neural network and training**: Relationships among port operations are complex since there are many nonlinear inter dependencies. For this reason, ANN are an appropriate tool for modeling this kind of problems. In this methodology we propose to use an Artificial Neural Network (ANN) with supervised training. Thus, this task consists of creating the architecture of the AI system, which means to select the final number of inputs to be used to train the net, number of targets, number of hidden units, number of layers, training algorithm, transfer functions and variable pre-processing algorithms. The fundamental aspects to be considered are presented below:
    - Data pre-processing: Pre-processing means transforming the input data into a format that eases the data process to the net. This task includes verifying, correcting and editing the input series in order to eliminate data entry errors, remove outliers or replace missing values, which will result in enhanced accuracy and speed in data treatment
    - Configuring the architecture: This means to select the number of layers, the number of input, output and hidden neurons, as well as the kind of transfer functions
    - Training the neural network: There are a variety of training methods. One of the most famous one is the so-called back-propagation, which bases the training in changing the initial weights until the error set as the difference between the outputs and the targets reaches a minimum prior to stop. During the training, the net may find out several local minimum, but the one that provides the absolute minimum error is the target to be reached
    - Evaluating the model: One of the strategies to determine if the training is satisfactory or if the process has to be performed again is through error measures such as the individual forecast error, mean error, mean squared error, mean absolute error (MAE) or the mean absolute percent error (MAPE)
    - Re-train if obtained results are not satisfactory: By doing this, the net changes its initial weights
    - Saving the configuration: When results are satisfactory, the configuration under which the minimum absolute error is obtained is saved. This configuration is the one used later to obtain forecasts, this is, to use the system

6. **Gathering input forecasts**: This forecasting system is possible thanks to the forecasting techniques of climatic variables and to the thorough scheduling and planning of port operations, which are used as inputs. These input data must be sufficiently reliable and, to check this, the goodness of both climatic and operational forecasts has to be evaluated. In the case of wind, forecasts are obtained for different time horizons that range between 36 and 72 hours, given in intervals of 3 to 6 hours. However, in operations scheduling, forecasts are not characterized and provided in the same way. For this reason, detailed analysis is needed of the operational data to be employed. In the first stages of implementation of this methodology, it is possible that several modifications need to be made for the results to be accurate and reliable. It is recommended that a detailed analysis of forecasting data is performed over a period of time, comparing them with historical samples, forecasts with a posteriori observations, etc.

7. **Obtaining operational parameter forecasts**: Once the neural net does work and provides acceptable results in the training stage, and input forecasts are available, it may be used to obtain forecasts.
8. **Check forecasts with records**: It is advisable in the first stages of the implementation, to check the forecasts with recorded information. If the forecasts are not sufficiently accurate, the system needs to be re-calibrated. This may occur for several reasons: i) network architecture being inappropriate; ii) training data being insufficient (i.e., the time series are too short); or iii) training data not producing variations in the parameter that is being observed. This last situation may be solved by applying methods for variable selection, such as self-organizing maps or genetic algorithms.
9. **Ready-to-use forecasting system**: Neural networks are dynamic systems and the model needs to be fed with new information for the neural net to provide forecasts based on the most varied situations as possible. On the other hand, as the majority of the information that is needed to apply this methodology can be found in the TOS, or is accessible through online databases, it is feasible to integrate the procedure as a tool into terminal control systems.

CASE STUDY: OBTAINING VESSEL PERFORMANCE FORECASTS

Problem statement

The studies that relate the effect that the climate drivers have over operations are scarce. However, it cannot be overlooked that such interaction produces modifications on the later, since one of them (the climate) has a strong random component and a source of variability and the other (the operational) is strongly deterministic. For this, and with the aim of illustrating the importance of this integration, the case study is developed in one of the most exposed subsystems to the environment: the loading-unloading subsystem. The goal consists of developing a forecasting system on the vessel productivity, which will be served in the next few hours under a set of operational and climatic conditions.

As it will be seen, this tool puts into value the effort put into the acquisition, storage and management of operational information at container terminals.

Starting data sets description

A Spanish container terminal provided the authors with operational information to be used in the development of the operational parameter forecasting model. Due to confidentiality reasons, the credentials of this terminal will be kept anonymous.

Operational Variables

A semi-automated container terminal provided us with operational data in two different formats:

1. Berth schedule: Graphic document that summarizes the main characteristics of the prospective operations to be performed on the quay. It shows the location of the current/immediate next vessels on the quay, the arrival order, the estimated stay time, the number of gangs that will be working on each service, the estimated arrival and departure times and vessel's code. In this methodology it is hypothesized that the information contained in the berth schedule is reliable and accurate. However, it has to be pointed out that this may not be right and reliability analyses should be performed in order to estimate the planning confidence intervals.
2. Operational report: Spreadsheet document that contains all the relevant information of a past operation arranged by a variety of topics, such as the gang information, the cargo information, the timing, and the productivity reached. Once the operation has finished, the terminal reports the service given, and saves the main descriptive parameters into a file that is used later to bill their clients for the operations performed, as to double check the data provided by the stowage society.

The files issued by the terminal reflect the cargo loading and unloading characteristics of container ships from January 2011 through October 2013, adding up a total of two years and ten months of services. A file per every vessel contains a summary of the relevant information of the operation performed. Vessels files are arranged by week, and the weeks by year. However, neither the contents nor the entries format is homogeneous for the period considered. Due to this fact, the analysis of every year of data must be done independently. Among the complete data set available, the most relevant information to this study is listed below:

- **Performance**: Specific information about the variables for loading-unloading performance measurement. In particular the timing (vessel arrival and departure, loading-unloading operation starting or ending); gangs (number of gangs simultaneously used in every shift); movements (Number of moved containers and kind such as the load, unload, special ones); and productivity (movements performed by the gangs per hour)
- **Gang Information**: Information regarding the gangs, that includes the kind of gang, a gang ID code, the movements split up by hour and shift, the starting and ending operations date, the number of containers moved, the surpass of estimated operation time, the total time dedicated to the operation and the productivity reached
- **Operational Report**: A summary of the timing and productivity of the operations. It includes the timing (vessel arrival, operations beginning and ending, time for pilot on board); the mooring information (vessel location on the quay, bollard number, vessel id, kind of service); the gang information (if early completion or late arrival); the gross and net timing and productivity; lost time and reason (if any crane fails); the number of containers moved and kind (load, unload, restows, gear boxes, ship-to-shore cone boxes, hatch cover, bays worked, crane split)
- **Stoppage Time**: It documents the duration of the stoppages that happened during the operation. They are classified according to mechanical failure; lashing/unlashing/others

Climatic Variables

The main goal of this case study is to illustrate how to obtain vessel productivity forecasts as a result of the interaction of the operations and the environment (this is, the climatic drivers) with the vessel or the loading-unloading equipment. Among all the climatic variables that are in direct interaction to the operational components of the loading-unloading operation, wind is the driver that affects the most to the cranes and the pending containers since they are the most exposed elements to this phenomenon. A Spanish Port Authority has provided wind data records. An anemometer located in the near area to the terminal, with no obstacles around it, has recorded these data. Records cover a period that ranges from June 15th, 2011 through January 13th, 2014 and provide information about wind speed and direction with a 1 minute time step (Δt[min] = 1). Mean wind speed time series for the entire period of records show maximum values that remain below 20 m/s, whereas the maximum wind speed series show maxima that reach 40 m/s (see Figure 2). Regarding wind direction, the most frequent coming direction is the East (E), secondly the North West (NW) and _nally the South-South East (SSE).

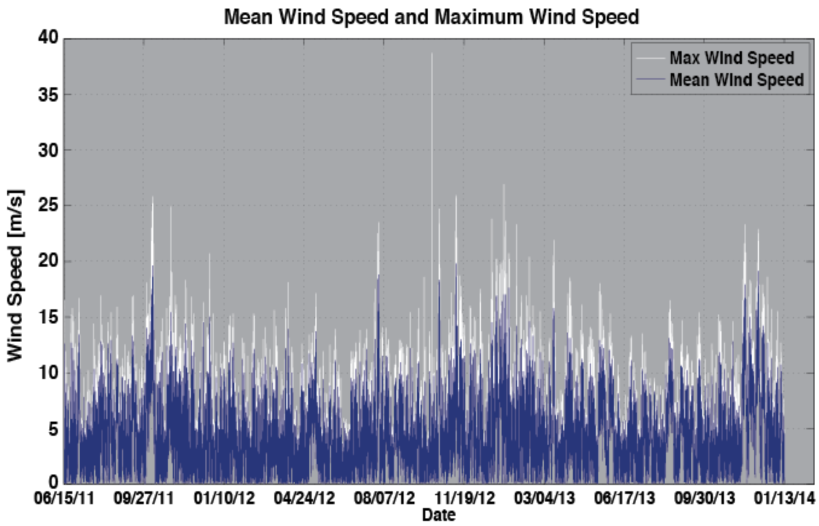

Figure 2: Wind time series recorded by an anemometer located in the surroundings of the container terminal, ranging from June 2011 through January 2014.

According to the starting and ending dates of the wind speed series and the operational reports, the period of time for which both of them are available ranges from October 2011 to October 2013.

Candidate input variables identification

During the implementation of this methodology one will be working with the neural network in two cases: on the training stage and once the net is validated, in order to obtain forecasts. In the development of this case study a supervised training neural network has been used. From now on, the term "forecast" will be used when referring to the data that comes from a validated numerical model since a numerical model has been used to obtain prospective values of the target variables (for instance, regarding wind speed) since the model has been matched and the predictions are highly precise. On the other hand, the term "planned" will be used for the operational variables that come from an estimated planning since their reliability degree has not been validated yet (only expected values provided) and thus it would be inappropriate to use the term "forecast" on them. The time interval for which the operational parameters are given is crucial. Some of the information gathered by the operational report is given in hourly time intervals whereas most of it is given for the whole operational period. Ideal analysis conditions would be using data sampled at a high frequency, since short time variations in productivity due to on-time events would be caught out. In this case, wind data satisfies this condition. However, for the operational variables, a single value is representative the whole operation so no short time variations may be found on it. Consequently, the time interval for which data is provided conditions the kind of neural network that is applicable to every case study. In this one, two main limitations have been found:

1. Wind records sampling frequency differs from that of the operational descriptive parameters. Consequently, no short time variations in productivity may be found, nor the causes that would produce them in short time steps
2. Because of the gaps of information found in the operational records, time-dependent analyses may not be used. This is important since some neural networks are based on regression analyses that correlate subsequent values of the training parameters to provide forecasts

The variables that must be selected as inputs to the neural network under the following criteria:

- Historical records must be available (to train the net), as well as schedulable ones (to obtain forecasts)
- The sampling frequency should be only slightly different for all the variables in order to not to induce errors or lose information when mapping the variables to adapt them to the most suitable time interval

By applying these considerations, the pre-selected variables are the arrival and departure dates and stay time, the number of containers to move, the number of gangs used, the vessel's location on the quay and the vessel's name.

The selection of these variables makes it necessary to operate the wind information to generate one representative value for the entire operation, in order to match its frequency to that of the operational variables. The reasons for this are that the opposite process is not advisable (matching the operational parameters to every wind data) since a lot of repeated samples would be introduced to the net and thus, it will discard the majority of it. In the other hand, the data set provided does not contain the vessels' dimensions despite of being an important descriptive parameter to consider since it physically makes the path followed by the container to be longer or shorter. Consequently, vessel's beam has been considered an additional training parameter. Vessel's beam has been searched separately on the Internet, based on the vessel's name contained in the operational reports. Thus the preliminary set of inputs is as follows:

- Berth time (timing characteristics): This is a parameter contained on the operational reports or calculated as the difference between the date and hour when the operation ends and the date and hour when the operation starts. Therefore, the starting and ending date and hour of the operation must be known. If timing information is not available, the entire vessel's information must be discarded.

$$\text{Berth time} = \text{End of Operation Date} - \text{Start of Operation Date} \tag{1}$$

- Number of containers to be moved (cargo-related information): In the operational reports it is broken down according to the kind of movement:

Containers = # Disch. + # Load.+ # Restows + # Gear boxes + # STS Cone boxes (2)

- Average number of gangs used (workforce-related information): The number of gangs dedicated to give service to a vessel varies with time. Thus, the average number of gangs used is a representative parameter of the workforce dedicated to the operation, and an indirect way of determining the number of cranes involved in it.
- Vessel's beam (vessel's size information): The authors found interesting to add a parameter that describes the vessel's dimensions. In this case, the beam size has been considered since it may affect the loading-unloading cycle speed. This data is not contained in the operational reports and has been searched separately. On the Internet it is possible to find a variety of vessel's parameters, such as www. marinetraffic.com, www.fleetmon.com, www.vesselfinder.com or www.shipspotting.com. Thus, starting from the vessel's name a search of vessel's beam has been performed. It has been incorporated to the MATLAB structure created where all the variables are arranged.

From the side of climatic variables, 1-minute sample mean wind speed, maximum wind speed and the corresponding directions are available. Thus, the mean wind speed, the root mean square of the wind speed (to introduce a parameter that takes into account the variability of the series) and its direction are the selected climatic variables to train the neural network. It should be noted that the sampling frequency of the wind data is much higher than that of the operational information. As previously mentioned, wind data must be transformed to generate a representative value for the whole loading-unloading operation. If higher sampling frequency for the operational variables is available, it is advisable to use them since this integration of the wind speed series may distort the effect that this climatic variable would induce in the productivity records.

Operational information error characterization

One of the greatest challenges when applying this methodology for the first time is to extract as much information as possible from the operational records since some fields pointed to have been completed manually and consequently many typos or incomplete fields have been found. Those errors or a lack of consistency in the data format makes it difficult to systematize the data reading, and thus, the data analysis. Consequently, the number of vessel's files that contain complete data sets of the variables to be employed is considerably reduced due to this fact with respect to the initial number of files. One of the most critical lacks of information is that of the starting and ending dates of the operations, since it prevents to extract the wind records corresponding to the vessel's service period, as well as to obtain the operation duration in the case that it is not properly filled in the corresponding cell. The main kind of errors found in the data set that it was given to the autors are:

- Inconsistencies in date and hour representation
- Errors in date and hour
- Missing starting and/or ending date/time
- Inconsistencies in vessel names".

As a consequence, the percentage of data that has been discarded for the above-mentioned reasons reaches 68%.

Wind Data Treatment

The matrix of features that will be employed to train the neural network must be completed with the wind information corresponding to the period when the vessel was operated. To this, wind data series must be transformed from continuous time series to one single interval that represents the wind characteristics for the operation time interval. Wind data has been recorded by an anemometer located near the terminal, at distance such that wind direction and module will not vary significantly in the forecasts given by the numerical models. This is important to consider since the neural network cannot be trained with wind data registered at a site where no forecasts are available, or where significant variations on its module or direction may occur.

Wind transformation starts with the application of the Powell law (Powell et al., 2003), conceived to obtain the wind speed at a height z based on wind speed information recorded at a different height z0.

In this case, wind data has been registered at a standard height (z_0[m] = 10), and the equivalent magnitude at a height z[m] = 30 corresponding to the approximate height of a pending container is needed. Powell law requires that a roughness factor weights the wind speed, to take into account the roughness of the environment surrounding the location of the instrument. Moreover a gust factor has been applied to the wind series to consider the turbulent nature of wind speed. Wind data series provided by the Port Authority give one data per minute, the result of applying a moving average window of 10 minutes to the raw series. This standard method filters the turbulent component of the wind. In order to include it, it is customary applying a gust factor to the averaged time series. This gust factor represents the deviation that exists between the mean wind speed in an interval and the maximum wind speed observed into that interval. Depending on the window applied to obtain the averaged values, a particular wind gust factor is applied. It may be obtained by means of the Durst curve (Durst, 1960; ASCE, 2007). In this case, a gust factor of 1.6 has been applied. As a result, the wind speed magnitude has increased with respect the original values. Moreover, in order to consider the variability of the wind data, the root mean square of the average wind series has been obtained. It will be employed as an additional training parameter. The wind information is then averaged, and one single value for every variable is obtained: average wind speed, rms of the wind speed and wind direction.

Neural Network Architecture Configuration

Neural networks provide fast, cheap and highly reliable solutions to forecasting problems. These techniques may be used to predict future observations of a given variable which in this case is the vessel productivity. This way, a model that generates a sequence of prospective values of productivity is created. Productivity forecasts are based in previous observed states of productivity (target samples), considering it as the result of the combination of vessel and cargo parameters, and wind conditions during the operation. On the development of this case study the Neural Network Toolbox from MATLAB has been used. One of the most important and time consuming stages of the design of a forecasting system based on neural networks is to select the input variables. However, only a few of scientific publications highlight the true importance of variable selection in the creation of a forecasting system (Maier & Dandy, 2000). This fact may lead to certain design flaws, since as the number of input variables increase, so do the computational complexity and the memory requirements. Consequently, the learning process becomes more complicated as multiple local minimum may be found in the error surface and thus it is difficult for the net to find the true optimum. The main steps for configuring a neural network are given below:

- Create the network
- Configure the network
- Initialize the weights and biases
- Train the network

First, expert judgment based on the current knowledge about the variables that would influence on the vessel's productivity was applied to select a number of candidate variables. Thus, from the available data, the variables that more likely would modify the value of the productivity are the environmental ones (wind speed and direction), the vessel's characteristics (beam size), cargo characteristics (number of containers) and the time needed to complete the operation (berth time). Initially, the authors considered to include the number of gangs dedicated to every vessel (to incorporate the work factor). Unfortunately, the high number of incorrect samples (empty values or NaNs) of this variable made it impossible considering it in the analysis.

Expert judgment makes the system to rely on a person, and thus it may result subjective and dependent on the case to be analyzed. Based on the previous reflection, the optimum approach to determine which input variables should be used as inputs is a combination of expert judgment and analytic approaches (Maier & Dandy, 2000). According to the restrictions on the number of available variables and on the hypothesis set about which the most influential variables among all the available ones on the vessel's performance value are, the variables that have been pre-selected to train the net are listed in the following:

- As Inputs
    - Mean Wind Speed

  - RMS Wind Speed
  - Wind Direction
  - Number of Containers
  - Berth Time
  - Beam Size
- As Target
  - Vessel Productivity Ranges

Due to the limitations found regarding the starting information, given that no time-correlation exists between the samples available, the net will be designed to classify the vessel performance level in three different intervals, defined according to the statistical analysis of the performance data carried out, that manifests that mean values are around 24 moves/hour, with a standard deviation of 3.94:

- Vessel's performance [0 - 20) moves/h: This interval is intended to classify the movements that fall below the mean productivity minus the standard deviation.
- Vessel's performance [20 - 30) moves/h: In this interval mean productivity values will be classified.
- Vessel's performance [30-max) moves/h: Data that fall in this interval corresponds to high productivity values. It will be interesting to analyze the combination of variables that leads to this situation, since it would help to adopt management strategies to take the operation to this range.

The number of layers and neurons are two characteristics that determine the size of neural network. This is important since the size is highly correlated to the performance of the network: the bigger the size, the more the free parameters that the net needs to calculate. If they are too numerous overfitting may occur. The number of network's parameters (weights plus biases) is one of the criteria that may be used as to select the architecture, since some authors state that the total number should not exceed one over six of the total amount of samples. According to this, given that the number of neurons in every hidden layer is 10, and provided that the number of parameters is assessed as the product of the input weights (a = 6), the number of outputs of every hidden layer (b) and the number of outputs (c = 1) one may have that the number of outputs of every hidden layer must be less than 3. According to the foregoing, tests were conducted under the recommended configuration of 2 neurons on every hidden layer would be the best choice. However, results were not satisfactory and the number of neurons in the hidden layers was increased to 10, configuration under which the errors obtained become stationary. Thus, it may be concluded that choice here was to test the different topology and find the one minimizing the error.

Second, from the pre-selected variables, the ones that will actually give additional value to the training must be determined. For this, an heuristic approach has been applied, that allows selecting variables in an orderly fashion. This approach is customary to avoid considering all the possible variable subset combinations. The two standard methods for variable selection are "forwards" and "backwards". In this occasion the "forwards" approach has been applied, and it starts with the search of the best combination of the input variables and by selecting them for the final model. The next model is built with the variable that gives the least mean squared error when training the net plus one of the remaining ones.

This process is repeated by building all the possible models with three inputs and selecting the third variable by means of the same criteria considered for the two previous ones. The process ends when no improvement in the mean squared error obtained is reached. With the aim to ease the display of these results the variables considered have been denoted as MWS = Mean Wind Speed, RWS = RMS Wind Speed, WD = Wind Direction, C = Number of Containers, BT = Berthing Time and B = Beam. As shown by Figure 3, the least error is obtained for a combination of 3 variables, namely the Number of Containers, Berth Time and Beam Size.

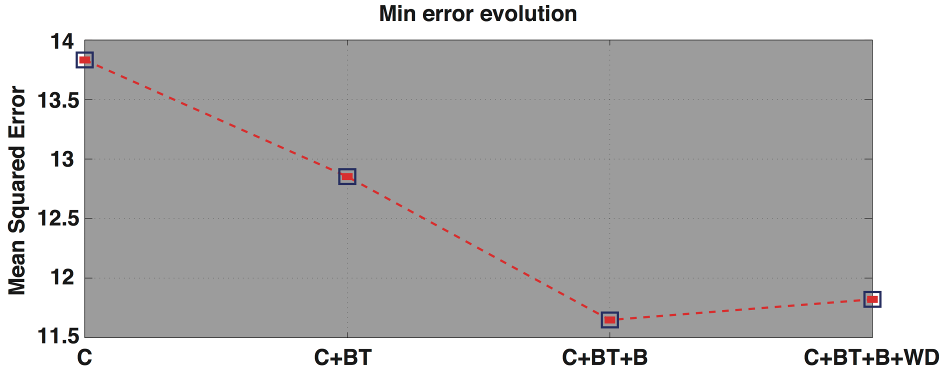

Figure 3: Error distribution obtained when training the neural network with 1, 2, 3 and 4 variables at a time, respectively

The training algorithm selected is trainlm, which is a network training function that updates weight and bias values according to Levenberg- Marquardt optimization (Marquardt (1963), Hagan & Menhaj (1999)). Trainlm is often the fastest backpropagation algorithm in the MATLAB toolbox, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. The activation and transfer functions used by the train algorithm are tan-sig. This function runs faster than the classic sigmoid function, thus accelerating the convergence of the backpropagation method (Vogl et al., 1988). According to the aforementioned, the neural network's architecture is composed by an input layer of 3 neurons, 2 hidden layers of 10 neurons each, and one output layer of 1 neuron (see Figure 4).

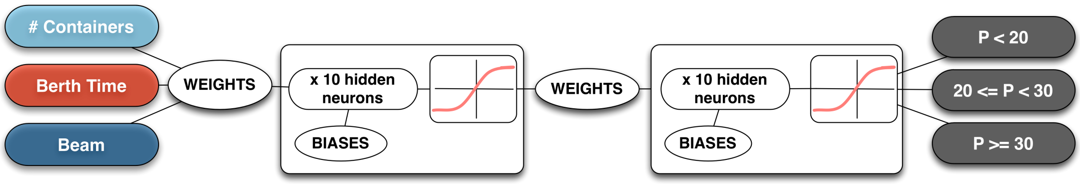

Figure 4: Diagram representing the neural network architecture employed

The most commonly used approach consists of dividing the available samples in three subsets: the training set, used to build and train the model; an independent set to validate the created model and to give estimates of its performance; and finally a test set, used to actually evaluate the generated model, where the outputs given by the net are compared to the targets given by the user. Poor forecasts might be expected if the validation set contains values that diverge significantly from the ones used on the training stage. For this reason, special attention should be paid to data division, being necessary that both data sets show values that are on the same range. As a rule, a 70% of the total number of samples is devoted to the training, a 15% for the validation and a 15% for the test. Next step consists of adjusting the training weights. To this, the backpropagation method has been used. The initial values of the weights and biases have been randomly generated by the algorithm. The final weights obtained after applying backpropagation have been saved to be able to use them to obtain prospective forecasts under this configuration.

Results

Training results are graphically summarized in Figure 5 that is described next. Additionally, error and performance analyses have also been carried out.

- Confusion Matrix : This matrix shows the data percentage that is properly classified by the net in relation to the targets given by the user. In this case study, performance level under 20 moves/hour has been assigned a value of 1, that of [20 - 30) is assigned the number 2 and performances over 30 moves/hour are given a 3. This codification eases the training process. As it may be seen, the net is able to properly classify performance values in a 84.1% of the cases, whereas the wrong classification reaches a 15.9%.

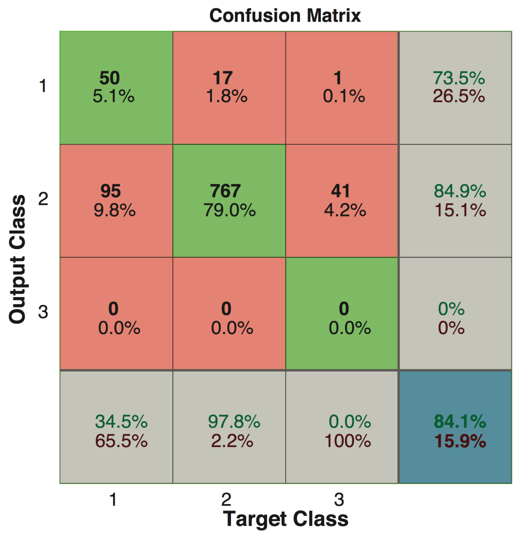

Figure 5: Confusion matrix

Once the net's calibration stage has been completed, the trained net's performance is validated, by using a set of independent samples from the ones used to train the net. It must be pointed out that the validation data set should not have been used as a part of the training in any way. For the algorithm validation a 48 samples input data set has been presented to the trained net, containing information relative to the number of containers, berth time and beam size. The forecasts obtained for the prospective operational conditions are shown in Figure 6. As it may be seen, the net has been able to classify properly a number of 38 out of 48 inputs, that makes an 80% of forecasting accuracy.

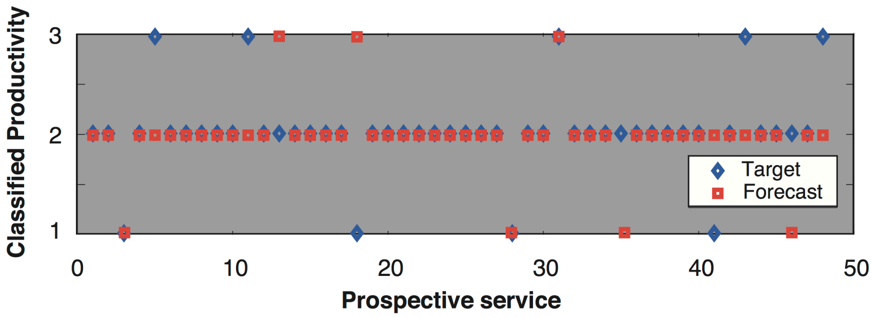

Figure 6: Classification forecasts for a new input data set of 48 samples

CONCLUSIONS

The main conclusions derived from the development of this work are enumerated below:

1. The methodology proposed is validated, and a classification of vessel performance forecasts has been obtained
2. Several typos have been found in the data records available, produced by human errors since the fields are filled manually in most cases. For this reason it may result challenging to automatize the reading of the data to later analyze them. The authors conclude that to standardize the operational data records format as well as to automatize the entries filling would ease the pre-treatment and analysis of past operations
3. The hypothesis about the influence of the climatic drivers on the operations has not been verified, since the wind data records corresponding to the vessels whose operational data is complete and accurate always fall below the stoppage limit speed of 20 m/s
4. The authors found that the classification forecast errors may be due to several reasons:
    - The limited amount and variability (poor quality) of operational information available. More records or additional training variables would be advisable to include
    - The absence of temporal continuity in the records due to information gaps
    - The deviations found between the planned operations and what is finally executed. In this regard the authors find interesting to put effort on characterizing the the deviations of the executed operations from the planned ones, to introduce this error as

a variable to be taken into consideration since this would allow improving the accuracy of the forecasts obtained

ACKNOWLEDGEMENTS

The authors are indebted to Puertos del Estado for financial support and to the Port of Algeciras Bay for providing us with both technical and data support.

REFERENCES

Adya, M., & Collopy, F. (1998). How effective are neural networks at forecasting and prediction: a review and evaluation. *Journal of Forecasting*, 17, 481-495.

ASCE (2007). *Minimum Design Loads for Buildings and Other Structures*. 1801 Alexander Bell Drive, Reston, Virginia 20191-4400: American Society of Civil Engineers.

Bilegan, I., Crainic, T., & Gendreau, M. (2006). *Fleet Management for Advanced Intermodal Services*. Technical Report Centre des Recherche sur les Transports (CRT).

Carbonneau, R., Laframboise, K., & Vahidov, R. (2007). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research*, 184(3), 1140-1154.

Celik, H. (2004). Modeling freight distribution using artificial neural networks. *Journal of Transport Geography*, 12(2), 141-148.

Durst, C. (1960). Wind speeds over short periods of time. *Meteorol. Mag*.,89 , 181-186.

Fancello, G., Pani, C., Pisano, M., Serra, P., & Fadda, P. (2010). Development of prediction models for container traffic. *In 12th World Congress on Transportation Research*.

Gosasang, V., Vatcharavee, C., & Supaporn, K. (2010). An application of neural networks for forecasting container throughput at bangkok port. *In 12th World Congress on Transportation Research.*

Hagan, M., & Menhaj, M. (1999). Training feed-forward networks with the marquardt algorithm. *IEEE Transactions on Neural Networks*, 5 , 989-993.

Maier, H., & Dandy, G. (2000). Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. *Environmental modelling and software*, 15 , 101-124.

Marquardt, D. (1963). An algorithm for least-squares estimation of nonlinear parameters. SIAM *Journal on Applied Mathematics*, 11 , 431-441.

Powell, M., Vickery, P., & Reinhold, T. (2003). Reduced drag coeficient for high wind speeds in tropical cyclones. *Nature*, 422 , 279-283.

Puertos del Estado (2001). ROM 0.0.: *General procedure and requirements in the design of harbor and maritime structures*. Public Works Ministry.

Vogl, T., Mangis, J., Rigler, A., Zink, W., & Alkon, D. (1988). Accelerating the convergence of the backpropagation method. *Biological Cybernetics*, 59 , 257-263.

Yan, B., Zhou, Q., & Gao, T. (2012). Analysis on throughput capacity of coal terminal by bp neural network. In ICLEM.

Zhang, G., Patuwo, B., & Hu, M. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, 14(1), 35-62.