Application of Fundamental Analysis and Computational Intelligence in Dry Cargo Freight Market

Athanasios Tsakonas[1], Emmanouil Nikolaidis[2] and Georgios Dounias
[1]University of the Aegean, Dept. of Business Administration,
8 Michalon Str., Chios, Greece,
[2]University of Piraeus, Dept. of Maritime Studies,
40 Karaoli-Dimitriou Str., Piraeus, Greece,
Phone: +30-271-35165, Fax: +30-271-93464
E-mail: tsakonas@stt.aegean.gr, mnik@hol.gr, g.dounias@aegean.gr

ABSTRACT: The aim of this work is to explore and estimate the short-term prediction efficiency, using two alternative approaches: the fundamental analysis on factors affecting the Baltic Panamax Index (BPI) evolution, and a computational intelligence approach based on neuro-fuzzy technique. In order to accomplish this task, we first analyze the basic routes that compose the Baltic Panamax Index. We estimate the supply and demand on the BPI standard routes, the GDP annual growth rate of main importing countries, and the other fundamental factors and thus we conclude for the up trend or downtrend in a short time basis. Next, we develop a computer based system, consisting of a neural network and a wavelet analysis and filtering system, using as system's input, BPI time series data for the past three years. The configuration of such system, involves the application of wavelets filtering as a system preprocessor, in order to identify the underlying trend of a BPI signal. Then, applying wavelet analysis enables us to further configure a neural network, which is finally used as the anticipation engine, of this system. Results showed that both techniques are capable to produce a short-term decision support in the maritime or financial sector. Nevertheless, more research on both domains might improve the anticipation power in either the fundamental or the computational intelligence approach. As a concluding remark, we suggest that the whole procedure may be a valuable tool in order to identify the capers freight market, or other maritime time-series data, as well.

KEYWORDS: fundamental analysis, dry cargo freight market, computational intelligence, genetic algorithms, neuro-fuzzy systems, time-series forecasting, fractal dimension, financial decision support

INTRODUCTION

In the complicated environment of the marine industry, the crucial question that every investor is invited to answer, refers to the choice of the right timing in order to make the most profitable decisions. Moreover, during the forecasting procedure the variables used are correlated and interacted in a way that the final outcome is questionable. Taking the aforementioned fact into consideration, the present paper aims to reveal the difficulties of the fundamental analysis and its inefficiency in relation with the issue of accurate forecasting. Specifically, we have developed a short-term forecasting which technique that is grounded on the self-learning fuzzy systems. That technique contradicts the classic economic theory based on fundamental elements such as the demand and supply and condition of dynamic balance. Our analysis is focused on the market of Panamax tonnage and the index of BPI (Baltic Panamax Index) where we are going to apply our forecasting techniques.

Considering nonlinear dynamic processes, the application of fuzzy systems seems inevitable. In a field where auto-regressive models were dominant during the past decades, and neural networks often failed to compete in real-world problems due to usual noise presence, self-learning fuzzy systems have been proved as an efficient tool for system identification, classification or prediction. Belcaro and Corazza acknowledge the difficulties which arise when artificial neural networks encounter a highly noise time series (in real world problems) contrarily to their success in deterministic chaotic series [3]. The ability of fuzzy rule-based systems in complex dynamic time-series data is demonstrated by Jang [13] where the hair dryer modeling problem is considered, comparing the results with ARX model prediction [18]. The fuzzy system achieved better performance by successfully modeling the non-linearity of such a dynamic system. Short-term prediction using fuzzy rule based systems is shown by Zardecki, where such a rule-based system is used for time-series forecasting [35]. The prediction involves finding x(k+1) given a window of past n measurements x(k-n+1),x(k-n+2),.., x(k). A main disadvantage in this procedure involves the selection of the lag size n which, when it is increased, leads to an exponential growth of the rule-base. It is often desirable a large number of inputs in order to increase the size of rule base offering to the system a high degree of freedom, however as Jang demonstrated, in such nonlinear dynamic systems, the number of inputs is not a crucial factor [13]. Another problem arises when performing multi-step prediction by applying feedback, which offers poor results due to error amplification, and consequently leads the output in convergence to a constant value. Nevertheless, the latter is a common effect to many prediction systems when feedback is applied. On the other hand, when noise is present in time-series data, fuzzy systems can achieve a quick training of the rule base, in contrast to other methods, such as neural networks which often require data pre-processing in order to avoid the noise adaptation [5].

An implementation of a self-learning fuzzy system may consist of an evolutionary training of the rule base and a neuro-fuzzy training phase for tuning the membership functions of the premise part As described by Kosko [16] the rule base may be coded in a fuzzy associative memory (FAM) matrix. After FAM matrix consideration takes place, it is easy to construct an efficient binary coding to represent this FAM matrix in bit-strings which will be used by a genetic algorithm to find the optimal solution [4]. The most prominent approach is to create a population of fuzzy rule-bases rather than a population of rules in order to avoid the cooperation vs. competition problem which arises from the fact that fuzzy rules compete with each other for the best systems output [7]. Short-term prediction may be easily transformed to handy decision making when fuzzy systems are applied in areas where the need of a system's output overwhelms a simple value prediction. Financial Market belongs to those sectors, where decision making has been an increasingly important factor for trading and investment professionals. Current assisting methods include among else the technical analysis of time-series data [19], various auto-regressive models [15], neural networks [12] and fuzzy system implementations [32, 29]. However, not all these procedures might claim the functionality of an integrated decision support system, while most of them aim at predicting a price evolution in a given time space, hence leaving the decision making as a primary responsibility to the trader. Moreover, the neural network implementations lack the system interpretation by storing the knowledge in hidden layers, which can be considered as black box knowledge by human observers. The attempts to translate hidden layer synapses, at present, are incomplete or insufficient [17]. In our approach, we explore the ability of a neuro-genetic fuzzy system, in providing the trader with a complete decision support, when dealing with short-term market determination by supplying a buy-hold-sell policy as a final output. In the next section, initially we discuss the fundamentals of the Baltic Panamax Index. Especially, we are going to estimate the equilibrium of the supply and demand of the Panamax vessels in order to determine the critical tonnage level, which leads to an up trend or a downtrend the Baltic Panamax Index.

Moreover, we are going to identify the factors affecting the BPI in an effort to create rules enhancing the efficiency of the fuzzy system. We believe that the best results could be achieved when we provide the system with accurate input based on the real market. Such input may be the tonnage supplied, the tonnage demanded for sea transportation, the price of new buildings, the price or/ and the institutional framework for scrapping, and more.

Then we present the configuration of our system referring to the problem identification and data selection. Then, the fuzzy implementation follows, describing the systems structure and training procedures adapted. Next section presents the simulation results, and the final section contains our conclusions drawn from this work.

FUNDAMENTAL APPROACH OF BALTIC PANAMAX INDEX

Analyzing the market of Panamax tonnage during the period 1998-2000 we can conclude that the particular market –in relation to the profitability- illustrates a significant plunge. Because of the substitution of the Panamax market from other tonnage categories, we examine two factors in order to obtain more precise conclusions. The first factor concerns the oversupply tonnage that drives the dry bulk market into a recession or ascension compared with the demand of dry bulk transportation. The following graph, which is derived from our analysis, depicts that every time the oversupply increases the profitability from the use of Panamax vessels declines (*Figure 1*).

The estimation of oversupply tonnage arises from the available tonnage in cargo payload terms minus the demand tonnage in tons on a daily basis. Thereafter, we oppose the behavior of the BPI index during the above-mentioned period (May 1998-May 2000) and we observe a gradual increase at the beginning of 1999 and afterwards (*Figure2*). That observation can be explained when we take into consideration the anticipated reaction of ship-owners to reduce the available tonnage in order to rectify the freight market. The desirable target is to find out the appropriate time period for investing and disinvesting in order to enable the ship-owners benefit from the volatility of the market.

A forecasting like this can be proved precarious for many reasons such as:

-The lowest level of the market that is an indication of investment in order the ship-owners profit from a future increase, is difficult to be calculated with accuracy.

-In reality, the market is influenced from many imponderable factors that are difficult to be measured and more difficult to forecast.

-The recession or the ascension does not appear simultaneously in the market and they do not affect in the same degree all the ship-owners.

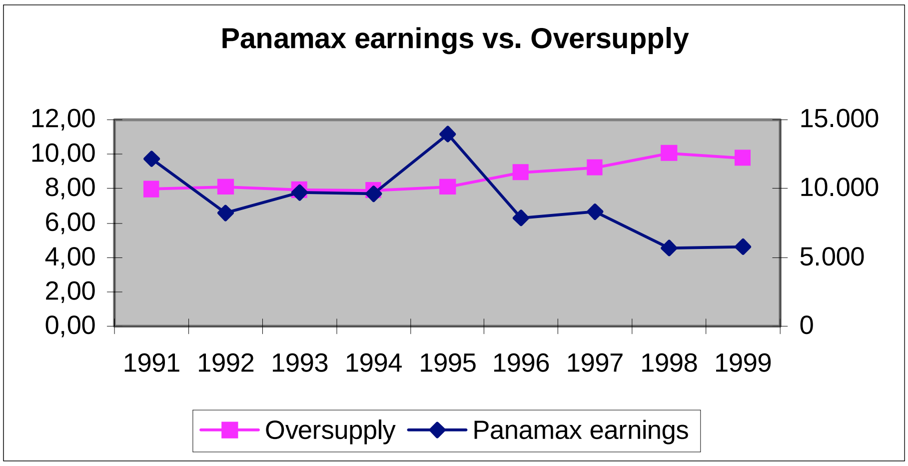

Figure 1. Panamax earnings vs. oversupply

For all these reasons, it is necessary to discover methods of protection from risks arose from the volatility of the market. An effective technique is the derivative products provided that the time of placing assures an efficient operation. Hence, there are many derivative products that are based on indices of particular markets. Taking into consideration that the fundamental analysis of the most critical variables of the market does not result in accurate conclusions for the future, we present the development of a fuzzy system which aims to create a method of helping the ship-owner in decision making process.

CONFIGURATION OF THE FUZZY SYSTEM

PROBLEM IDENTIFICATION AND DATA SELECTION

Aiming at offering to the trader a well-determined strategy, we suggest a proposal for buying or selling a BPI futures quantity and then perform the inverse transaction in a limited number of days. Therefore, this need is translated in predicting approximately the price evolution in the corresponding time space. The design of such a decision support system requires for practical reasons as system output, the cumulative return for two working days, which is actually the time interval in which we request the prediction. These reasons derive from the type of available data, which in fact are daily returns. While working with daily BPI returns, any prediction produced by such a system may be realized the very next working day, thus leaving to the trader a very limited interval to earn income to realize earnings when only one day would have been selected as prediction period. On the other hand, it has been demonstrated that considering these time-series data as a non-linear dynamic system, effective prediction becomes harder as the desired forward time interval is increased . The length of this time series prediction depends of a qualitative measure expressed by the Lyapunov exponent [20, 22, 17]. Therefore in our system we consider the requirement by the trader of both the owning of a relatively large quantity of a BPI futures and a corresponding capital, which are split in smaller pieces and used for the above mentioned transactions. Consequently, our system is proved to provide an efficient policy for such dealing actions. However, the simulation results also demonstrate that our system approach is able to assist a trader when no initial investment to the index has been accomplished, in other words meant that the trader may take advantage only in “index up trends” even in a strong bearish market. As a result, in all tested cases, our system’s policy was proved to be superior to a buy and hold policy. When the desired system output has been selected (e.g. cumulative returns in two working days) after the phase of problem specification, the next stage is to select the system’s input. In general, when considering daily returns as a non-linear dynamic system it is usual to select values from the past [13]. The selection of the appropriate inputs may be accomplished by an exhaustive search among all possible inputs in an input vector. By this procedure we train and test independent fuzzy systems selecting one input from the past and then, after the training phase, we examine their root mean square error (RMSE) on the test set. The input that offers us the minimum RMSE is kept and the procedure restarts using two inputs: first, the input that in the previous run offered the smaller RMSE and as a candidate for the second, any of the rest ones. Then, the system having the minimum RMSE again is kept and the procedure goes on incrementing the number of inputs. By adding more inputs it is naturally expected that the RMSE will be lower, deriving from the rule base enlargement which offer a higher degree of freedom in the system [14].

However, regarding the evolutionary search method applied by genetic algorithms as part of the training process, computation time evolves exponentially by adding inputs, and therefore, when no parallel computational architectures are used, it is preferable for practical reasons to keep the number of inputs relatively low. Additionally, as stated above, the effect of having lower RMSE by incrementing the number of inputs, is not always observed, when the prediction refers to such dynamic systems. As a next stage, the selection of the appropriate training vector comes into consideration. In fact, we believe that it is a hard task to accomplish. The training set should contain a number of input vectors at least equal to the number of rules, in order to take advantage of the anticipation power of such a rule-based system. Another way to define such a proper training set may be derived by examining the qualitative characteristics of the training data. Thus, we may select an arbitrarily large set of past values and then we can examine its fractal dimension using self-similarity inspection methods [9, 10, 8] such as dispersional analysis [1, 2]. Dispersional analysis is suitable for data as daily returns, while it is designed to analyze fractional Brownian noise . Kozma and Kasabov suggested also the use of fractal dimension as a qualitative measure in terms of determination of the structure of a fuzzy neural network [17]. Considering large train sets of daily returns (e.g. two-three years) the fractal dimension approaches a value that characterizes stochastic signals. Therefore, in these large data sets, the process resembles to a stochastic one. However, by decreasing the vector size, occasionally a self-similarity in this signal is revealed, corresponding to different market evolving periods. As expected then, the fractal dimension is reduced, and consequently the Hurst exponent of these data is increased, showing that, in these smaller periods, the process might be considered more as a persistent than a stochastic one. Thus, adapting a data set with a relatively high Hurst exponent, and therefore "more" self-similarity, offers us a better probability of non-conflicting expected market behavior, based on these past data. It is worth to note here that these methods may sometimes offer ambiguous results, while it is known that they frequently lack the ability to distinguish between dynamic and stochastic processes, hence sometimes a pure stochastic signal could be misclassified as a dynamic one.

FUZZY IMPLEMENTATION

The implementation proposed in this paper describes a *Mamdani* or *zero-order Takagi-Sugeno* fuzzy system [14], in which, both its linguistic and defuzzificated output are used. The defuzzification scheme calculates the centroid of fuzzy area output for the crisp value extraction, and this selection was done as this procedure consists the most widely adopted defuzzification strategy. The defuzzificated output is then used both in the training phase and in the estimation of a desirable future equity price. The linguistic output determines to the user the action to take place, according to the system's configuration and training status. The selection of the premise part should consider the fact that daily BPI returns are characterized by a large presence of noise[1]. Hence, a small number of antecedent sets describing the basic characteristics of a value (e.g. low/zero/high) is more desirable than a high resolution system. Zardecki has demonstrated that when applying a fuzzy system in noisy dynamic time-series data, its prediction ability is reduced when a fine resolution is adapted [35]. In other words, such a system fails to measure the dynamic properties of this signal because its chaotic structure is truncated due to the noise existence that infers with the system. Assuming that the noise follows a normal distribution, Gaussian bells shapes seem most appropriate for the premise part [14]. The Gaussian shape is derived by the following formula:

$$\text{Gaussian}(x;c,a) = e^{-\frac{1}{2}\left(\frac{x-c}{a}\right)^2} \qquad (1)$$

Where *c* is the membership function's center and *a* is its width. The reason why we selected to train such a fuzzy system is that human domain expertise in Financial Market is incomplete or evovling through time, therefore we cannot explicitly obtain always an accurate configuration. In order to proceed when training a fuzzy system, the objective function is derived by the output of a second fuzzy system, called hereafter as *objective fuzzy system.* The training procedure may be summarized for a fuzzy system consisting of *n* inputs and an objective fuzzy system consisting of *k* inputs, in the following steps:

1. *Select a proper training data set*[2].
2. *Select the vector size for system inputs and outputs*[3].
3. *Apply evolutionary training using genetic algorithm for rule-base determination*
4. *Apply neuro-fuzzy training for membership function refinement*

Each training vector consists of a time window containing subsequent values and its size is equal to the sum of vector sizes of both fuzzy systems' inputs. This objective function is calculated by applying the objective fuzzy system

[1] For the noise determination in financial markets the reader is referenced to [6]
[2] based on the observations of the previous paragraph
[3] based also on the observations of the previous paragraph

into the last values of the training vector. This function is created based on the cumulative prediction returns over a future step and may be easily derived by a heuristic model which extends as a chain rule the following set of rules in the form of a decision output of the objective fuzzy system, when one day prediction is needed. It may be easily shown that the possible outcomes using this concept, are given by the following formula:

$$U = a * (g - 1) + 1 \tag{2}$$

where, a is the desirable forward number of days (and so the objective fuzzy system inputs), g is the number of membership functions (number of premise sets[4]), and U the possible outcomes. By assigning to these outcomes a crisp value we may obtain a defuzzificated output when the objective value is applied to the last values of a training vector. In general, the above scheme, may be considered as a common sense set of rules, if forward price returns were known *a-priori*. The concept behind the neuro-genetic training is to obtain a rule base as well as membership functions' shapes for a fuzzy system, which will have the same or almost the same[5] defuzzificated output with the objective fuzzy system applied to forward values using this common sense set of rules. To accomplish this task we selected to apply the genetic algorithm for the configuration of the rule-base while we may not use any derivative-based methods. We coded the fuzzy systems inputs in a fuzzy associative memory matrix. Hence, the number of all rules is derived by the well-known formula:

$$R = g^{n} \tag{3}$$

where, g is the number of premise sets, n is the number of past days (the fuzzy system inputs) and R is the number of rules. The binary representation of this rule base in a chromosome leads us to the adoption of a chromosome size as shown below:

$$b = x : \; 2^{x} > U > 2^{x-1} \tag{4}$$

where, b is the needed size of bits to represent a rule and U is the number of possible outcomes (also the number of crisp output values). It is worth to note here that depending on the number of days selected for the two fuzzy systems, the possible outcomes may be different. For example, a selection of two days ahead prediction, requires for the objective fuzzy system five possible crisp outputs (assuming three antecedent sets), while the selection of three days as input to the (main) fuzzy system requires seven crisp outputs (assuming again three antecedent sets). However, training is still applicable, by spreading the crisp outputs of both fuzzy systems in the same interval. In this example, the values for the objective fuzzy system would be (-2,-1,0,1,2) and for the (main) fuzzy system would be (-2,-1.33,-0.67,0,0.67,1.33,2) approximately, when a (-2,2) space interval was selected. After trials in various genetic parameters, we considered that a population of 100 chromosomes with a crossover probability 0.6 and mutation probability 0.01 offered quick adoption of the desirable rule base. The selection technique was the stochastic sampling with replacement (SSR). The fitness values were rescaled after each iteration in order to avoid premature convergence.The heuristic variable point crossover[6] scheme presented in previous work [30, 31] was adopted here too, while it was proved more efficient than any fixed point scheme. The genetic procedure tracks the optimum chromosome throughout the operation and when the desirable criteria are met it adapts this chromosome as the best rule base. Each individual's fitness is calculated in every iteration by the following algorithm:

1. *Set t=k+n*
2. *Acquire a time window x(t-k-n),..,x(t) of the training set as one training vector*
3. *Obtain the defuzzificated output of the objective fuzzy system on values x(t-k),..,x(t-1),x(t)*
4. *Obtain the defuzzificated output of the fuzzy system on values x(t-k-n),..,x(t-k-1),x(t-k)*
5. *Calculate the square error between the above values*
6. *Set t=t+1*
7. *Repeat steps 2-6 until the training set is exhausted*
8. *Calculate the Root Mean Square Error of the two fuzzy systems.*

The next training stage involves the neuro-fuzzy training. The rule base configuration affects dramatically the output a fuzzy system, therefore it was preferred the application of this procedure before the neuro-fuzzy training which is used for the fine tuning of membership functions. In each iteration of the neuro-fuzzy process, the system adapts better locations and sizes for the membership functions using error backpropagation. We implemented the model described by Nauck and Kruse [26], and additionally the delta calculation we adapted for Gaussian membership functions is presented below:

$$\delta_c = \sigma \delta_R a \,\mathrm{sgn}\left(o_x^{'} - c\right) \tag{5}$$

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[4] In the example above, three

[5] For a given training data set, the success a low RMSE during the training phase, depends on the model selection itself.

[6] By this heuristic variable crossover scheme we started with two-point split and we doubled the points each time the average error spread was reduced by half. In most cases examined of this work, the algorithm achieved faster convergence leading eventually to a greater than or equal to 16 point split.

$$\delta_a = -\sigma \delta_R a + \delta_c \tag{6}$$

According to the model initial notation, see [25], we consider here t_i to be the objective value, o_{c_i} the output value, $\delta_R = o_R(1 - o_R)\sum_{c \in U_3} W(R,c)\delta_{c_i}$, where $\delta_{c_i} = t_i - o_{c_i}$, and o_x the output such that for a specific rule $W(x', R)(o_x) = \min_{x \in U_1}\{W(x,R)(o_x)\}$, where U_1 is the input layer for this system, U_3 is the output layer and *R* is the rule node. Finally, in the equation (2.5) and (2.6), δ_c is the delta for the parameter *c* (center) of the membership function and consequently δ_a is the delta for the parameter *a* (width) of the membership function. In our implementation and training we applied on-line training process with learning rate 0.0001 for 100 iterations. When the training has been finished, the prediction efficiency is subsequently checked after each forecasting step using the square root deviation of the testing set [21]:

$$e_{dev} = \sqrt{\frac{1}{n}\sum_{1}^{n}(o_n - \rho_n)^2} \tag{7}$$

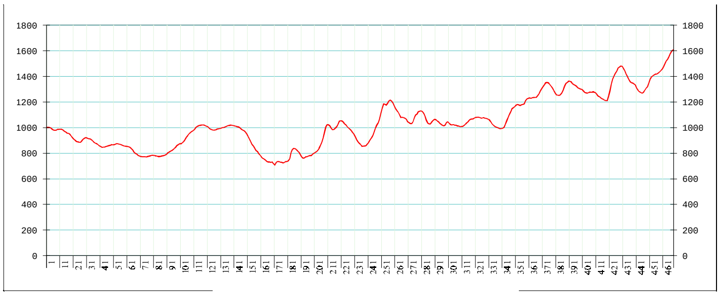
where o_k and p_k are here the objective and predicted system defuzzificated values, while *n* is the size of the set tested so far. When this value exceeds the following statistical measure, the anticipation power of the system is considered reduced, hence training should be performed again:

$$\rho_n - o_n > \bar{e} \pm 3e_{dev} \tag{8}$$

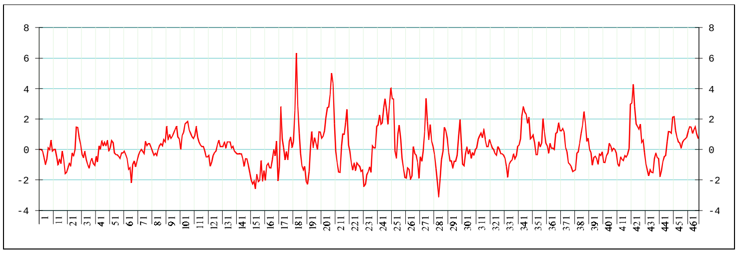
where $\bar{e}$ is the mean error of the training set.

RESULTS AND DISCUSSION

In the following section we will present the procedure followed for noisy time-series signal, such as the BPI daily returns. Extensive work can been found already in deterministic non-linear models [13, 17], therefore the scope of this paper is primarily the demonstration of the efficiency of this system in a real-world problem such as the BPI-financial decision support.



BPI daily values



Daily Returns

Figure 2. Train set value evolution (upper graph) and corresponding daily returns (lower graph) of BPI From 06/05/98 to 07/05/2000

The selection of a proper training set may be crucial for the system performance therefore the procedure followed is described in detail. *Table I* demonstrates the self-similarity revealed in shorter periods. Typical one-dimensional stochastic signals have a fractal dimension of 1.5 and a Hurst exponent of 0.5. The values obtained by applying dispersional analysis clearly indicate that in the small period, the signal is characterized as strongly persistent (Hurst exponent >> 0.5. The values are compared with pure stochastic signal in order to ensure the efficiency of the algorithm. A selection of a train set with a low fractal dimension mirrors the fact that this self-similarity may represent less conflicting training vectors, hence the rule-base generated will be consisted of signal's representative rules.

Table I. Hurst exponent and fractal dimension as a measure of signal persistence.

BPI From 30/08/1999 to 29/2/2000 (148 values)	**Stochastic Signal (148 values)**
Hurst Exponent : 0,619417301631029 Fractal Dimension : 1,38058269836897	Hurst Exponent : 0,488387532926413 Fractal Dimension : 1,51161246707359

Table II demonstrates another qualitative measure. Roughly speaking, the largest Lyapunov exponent indicates how 'chaotic' may be considered a signal, in terms of exponential relations between adjacent values. An absence of a positive largest Lyapunov exponent indicates a non-chaotic signal. However, using this method, purely stochastic signals or high-noisy periodic signals may also be misclassified as chaotic ones. The algorithm implemented here is described by Wolf et al., see [33].

Table II. Largest Lyapunov exponent[7] as a qualitative measure between different financial time-series.

BPI From 30/08/1999 to 29/2/2000 (148 values)	Lyapunov Exponent : 0,487602295458679
Logistic Equation (first 256 values)	Lyapunov Exponent : 0,993009722159705

This algorithm output is tested with the logistic equation in which the largest Lyapunov exponent is known to be equal to 1.00. The small deviation from this value (1.00) may be translated as a result of the initial transition effects. The BPI signal has low sensitivity to initial conditions as compared to the logistic function, which is a property making the forecast by the system more accurate. After completing the signal analysis, we train a fuzzy system, according to the specifications presented in the previous sections. In order to apply a simulation process, several considerations must take place. At first, when the system proposes a transaction, the transaction price is assumed to be the last days closing value, which in most cases was easily achievable during the next day, based on the intra-day volatility that BPI exhibit. Then, a simulation strategy should be applied based on the different strength of the systems proposed action. An example of such strategy is shown in Figure 3. Finally, we allow short selling[8], and for every transaction proposed by the system a complementary transaction is done in two days interval (the prediction interval of such a system) enabling in this way the zero-money deposit for the trader[9].

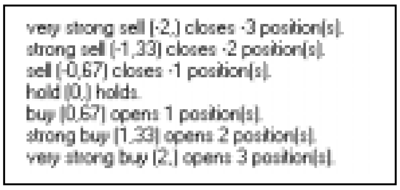


Figure 3. Simulation strategy applied for the financial decision support

In Figure 5, the cumulative returns are shown for both the training set and the test set. The results were compared with the buy and hold policy (an investor's policy). In this example, during the testing phase simulation, the statistical measure was not exceeded, hence the need for performing again training was not encountered. It is worth to note here, that in a real-world implementation the application of such a system could offer even better results, due to the flexibility for the trader to achieve better prices than the simulation ones, based on intra-day slight deviations from closing prices.

[7] The parameters for the largest Lyapunov exponent computation were set as: Time delay=1, embedding dimension=2, grid resolution=20, time step=1, evolution time=3 , minimum separation at replacement =0.0001, maximum separation for replacement =0.05 , maximum orientation error=30

[8] 'Short' selling is considered when an investor or trader sells a quantity of futures without having previously this quantity in his possession.

[9] In a real-world implementation, the application of this system is considered in minimum transaction volumes, in order to avoid the interaction of these transactions with the predicted trend, which may alter the anticipated price evolution.

Figure 4 shows a part of a generated rule base indicating the different short-term behaviors of this equity and Figure 5 shows the trained premise sets for the system's third input (Day 2).

10: If Day 0 is zero and Day 1 is low and Day 2 is zero then Action 0 is strong buy [1,33]
11: If Day 0 is zero and Day 1 is low and Day 2 is high then Action 0 is sell [-0,67]
12: If Day 0 is zero and Day 1 is zero and Day 2 is low then Action 0 is strong buy [1,33]
13: If Day 0 is zero and Day 1 is zero and Day 2 is zero then Action 0 is sell [-0,67]
14: If Day 0 is zero and Day 1 is zero and Day 2 is high then Action 0 is buy [0,67]
15: If Day 0 is zero and Day 1 is high and Day 2 is low then Action 0 is strong sell [-1,33]
16: If Day 0 is zero and Day 1 is high and Day 2 is zero then Action 0 is sell [-0,67]
17: If Day 0 is zero and Day 1 is high and Day 2 is high then Action 0 is strong buy [1,33]
18: If Day 0 is high and Day 1 is low and Day 2 is low then Action 0 is sell [-0,67]
19: If Day 0 is high and Day 1 is low and Day 2 is zero then Action 0 is buy [0,67]
20: If Day 0 is high and Day 1 is low and Day 2 is high then Action 0 is very strong sell [-2,]
21: If Day 0 is high and Day 1 is zero and Day 2 is low then Action 0 is strong sell [-1,33]
22: If Day 0 is high and Day 1 is zero and Day 2 is zero then Action 0 is hold [0,]
23: If Day 0 is high and Day 1 is zero and Day 2 is high then Action 0 is very strong buy [2,]
24: If Day 0 is high and Day 1 is high and Day 2 is low then Action 0 is strong buy [1,33]
25: If Day 0 is high and Day 1 is high and Day 2 is zero then Action 0 is hold [0,]
26: If Day 0 is high and Day 1 is high and Day 2 is high then Action 0 is very strong buy [2,]

Figure 4. Part of the generated rule base

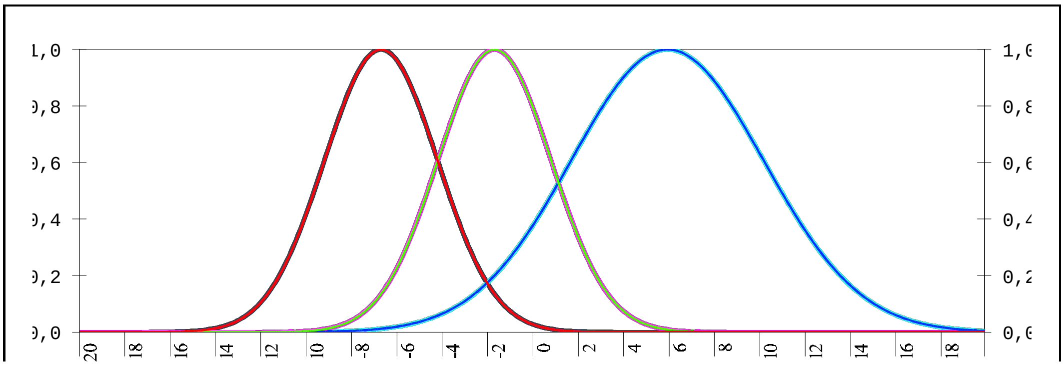


Figure 5. Trained premise sets using the neuro-fuzzy technique for Day 2 (third system input)

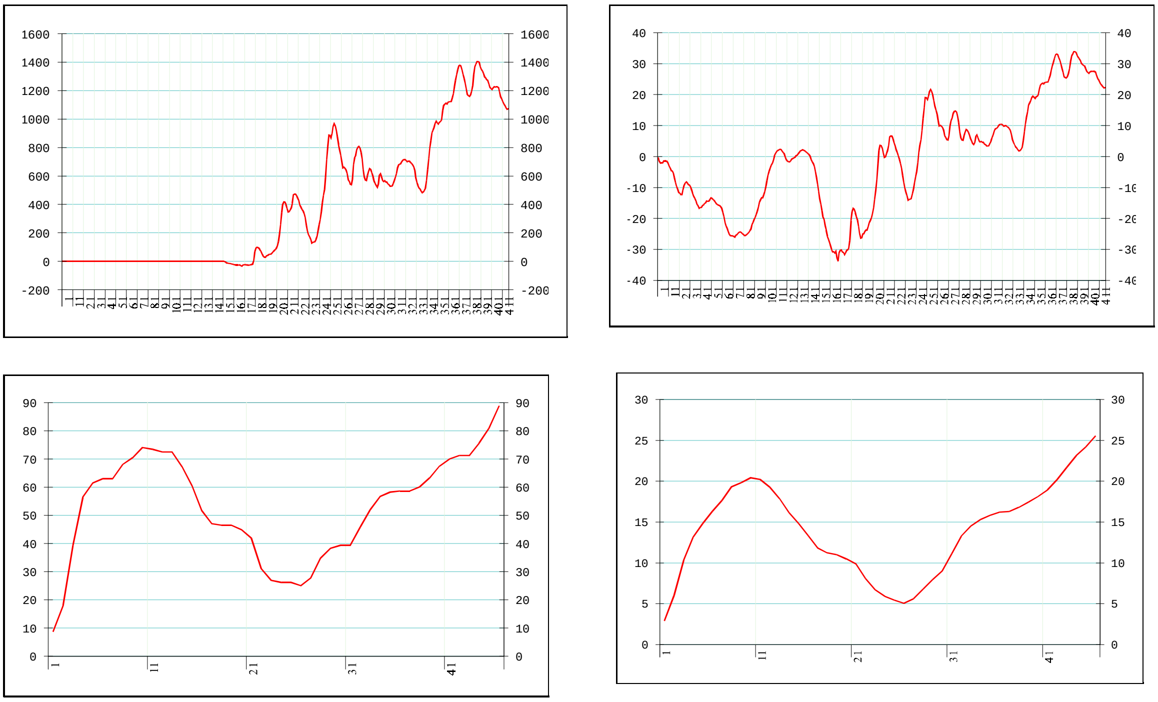


Figure 6. *Upper left*: cumulative returns on train set for system prediction, *upper right*: cumulative returns on train set for buy and hold policy, *down left*: cumulative returns on test set for system prediction, *down right*: cumulative returns on test set for buy and hold policy.

We should remark three interesting results, which were common to all cases, and may deserve further investigation:

- The cumulative returns of this neuro-genetic fuzzy system's prediction never fell substantially below zero.
- This system proved in our tests to be capable to increase the cumulative returns even in the case of downtrend (bearish) markets.

The system was capable also to offer positive results for the relatively large testing periods without performing training again, while also the statistical measure was not exceeded.

CONCLUSIONS AND FUTURE WORK

In this work we have analysed a subcategory of the marine industry such as the dry bulk Panamax tonnage market and to indicate the problems that the operator has to confront in order to estimate accurately the time of his/her entrance or exit from the market.

Since, the real market is reflected through the BPI index, we approached the issue of short-term forecasting by the development of a self-learning fuzzy system and we estimated its efficiency. Additionally, we developed a tool which combines data of the real market in a way that the final outcome leads to an integrated decision support system with the assistance of the computational intelligence.

The core of this methodology was a neuro-genetic fuzzy system, which achieved very efficiently to eliminate the undesirable effects of the noise content of the signal, and also to operate on the underlying non-linear dynamic (chaotic) trend. In order to improve the effectiveness of such a system, careful selection of training data was applied based on non-linear dynamic qualitative measures. The overall system proved capable of performing a trading policy, offering both capital preservation and positive returns even in downtrend markets.

Concluding our analysis, we would like to stress out that the best result can be achieved by combining the computational intelligence with the analysis of the basic variables of each market. Furthermore, we should highlight that the dynamic forecasting systems can be used only complementary since, they are not able to substitute the analytical mind of a human being

Further research could be directed in the use of alternative evolutionary methods like tournament, elitist strategy etc., as well as testing the efficiency of different membership functions like Cauchy, Close Sigmoidal shapes etc., while also different metric and statistical measures of chaos could be applied (Grassberger-Procaccia dimension [11], Termonia-Alexandrowicz dimension, information dimension etc.).

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