RESEARCH ARTICLE

Financial Forecasting using Neural Networks

Banica Logica*, Pirvu Daniela, Hagiu Alina

University of Pitesti, Faculty of Economics

*Corresponding Author: E-mail: *olga_banica@yahoo.com*

Abstract

Inspired by the human brain structure and functions, artificial neural networks (ANNs) have a large application area in forecasting the economic phenomena. In the actual context, when the economic crises affect the entire business world, it is necessary that financial tools and application software cooperate in order to forecast the market trends with the aim to reduce the insecurity and provide solid growth for the companies in the future.The aim of this paper is the theoretical presentation of a forecasting model based on neural networks and a study case regarding the evolution of the company OMV PETROM S.A., one of the largest companies in Southern and Eastern Europe. For the experiment we used various implementations of the neural network algorithm offered by GMDH Shell software and the financial consolidate statements of the company during 2005-2011, in order to obtain a forecasting of financial indicators for 2012.

Keywords: *Corporate management, Financial indicators, Forecasting software, Neural networks.*
JEL Classification Codes: C53, C61, D21, G1

Introduction

Scientific research aimed at gaining insights on the future, related to a high-importance domain such as business evolution, has the main goal of finding a way to minimize the risks and reduce the insecurity pressure in a business world affected by the economic crisis. Companies have turned to knowledge, processing and analyzing information in order to realize short-term or long-term forecasting based on powerful software applications.

Information gained with these tools, by using time-series data and choosing the highest impact variables, can be processed with different technologies (neural networks, knowledge-based systems, genetic algorithms) and will help detecting trends in the financial evolution of a company, a topic of high importance for top-level managers, helping them in taking the best decisions possible.

To forecast the evolution of financial indicators under the influence of important business environment factors and to making a new business plan following the prediction, the company management includes three financial statements: profit and loss, balance sheet, cash flow. Obviously it is important to understand these financial management tools, the way they interact, because they offer the performance measures of profitability, liquidity and economic growth over the planning horizon chosen [2].Forecasting is an old concept, but the technologies to implement it are more and more complex (neural networks, knowledge-based systems, genetic algorithms), implemented as software applications used for gathering and analyzing data about a company, in order to find a pattern, to test and validate the solution on actual data and to predict the future (generic referred as forecasting software).Based on the financial consolidate balance sheets of the OMV PETROM SA company during the last 7 years (2005-2011), we applied a neural network model in order to obtain a forecasting of financial indicators for 2012. Finally, we made a comparison of the accuracy of predictions on validation dataset. The paper is organized as follows: in the next section, the basic concepts and modeling approaches of the neural networks in forecasting models are presented. In section 3 is described the proposed financial model and in section 4, the model is applied to a company using two software implementations based on ANNs and the forecasting models are compared. The final section contains the conclusions of the actual studies and some considerations about the future work.

Methodology:Artificial Neural Networks in Forecasting Models Meeting two Concepts

Forecasting and Neural Networks

Business dictionary defines the concept of *forecasting* as „a planning tool that helps management in its attempts to cope with the uncertainty of the future, relying mainly on data from the past and present and analysis of trends" [9]. There are fundamental differences between forecasting and prediction: forecasting is objective, scientific and reproducible, while prediction is subjective, generally intuitive and non-reproducible [16][18].

According to [13], „Artificial neural networks (ANNs) are one of the most accurate and widely used forecasting models that have enjoyed fruitful applications in forecasting social, economic, engineering, foreign exchange, stock problems".

Neural network architectures can be trained to predict the future values of the dependent variables. The characteristics that recommend the ANNs for scientific forecasting are.

- The capacity to approximate any continuous function, with a target of accuracy;
- The usage of nonlinear methods, similarly with most of real systems;
- Data-driven self-adaptive methods, opposed to the traditional model-based methods;
- The capacity to generalize the forecasting process, after learning the data set;
- The parallel-distributed processing of data.

The most popular model is the one hidden-layer feed forward network [21]. In figure 1 is presented the model structure, containing three layers of processing units connected by acyclic links. The role of the input layer neurons is to transfer the input data to the hidden layer as it doesn't have an activation function. Neurons may be linked to further neurons (synapses), designing multiple layers configuration. Weights and numbers of layers are typically optimized over an estimation interval (training set) and are then used for prediction on the test dataset and on the selected architecture.

Starting from certain assumptions, forecasting projects into the future the trends using different models, such as: neural networks, Delphi method, exponential smoothing, moving averages, and regression analysis.

Our experiment is based on *neural network - time series* model, used for forecasting the future behavior of variables. Neural networks are nonlinear sophisticated modeling techniques, able to modeling complex functions. They can be applied to problems of prediction, classification or control in a wide spectrum of fields such as finance, medicine, engineering, and physics. Neural networks have been widely used as time series in forecasting: most often these are feed-forward networks which employ a sliding window over the input sequence [15][19].The algorithm used in the case study presented is *neural networks*, usually choose when is known the exact nature of the relationship between inputs and output. A key feature of neural networks is that they learn the relationship between inputs and outputs through training, so we split the input variables on two groups, having the training/test ratio: 75% / 25%. The accuracy of expectations which can be formulated about the future, allow managers to allocate resources in order to maximize profits. The precision of information depends on sources and volumes of collected data, the selection of descriptive variables for chosen predictive model. Even if some factors are not relevant, the model assesses the most important and assigns them much more weights [2]. In this manner, the relevance of the results depends on the development of the following three stages of forecasting system:

- Accessing a large amounts of historical data and giving an assign an appropriate weight to each factor within the input data;
- Using forecasting software to prepare data processing - means the import of data into the application, separate the training data from test data, establish the number of neuron layers and the output variable(s). In case of non-continuity or outliers of dataset, additionally, it must be specified a method for covering. If the software detects missing values, they must be replaced, by an interpolate value, by an average value or by zero etc. If outliers are uncovered, they must be removed.
- Choosing the appropriate model for forecasting and evaluation the accuracy of prediction – is a matter of trust and of target focused. Current forecasting software gives enough information (graphs, reports, performance, indicators etc) to an experimented manager in order to make an evaluation of the accuracy of the results. It depends on his option to share input data into the learning and the validation set and also, on his choice regarding the configuration of neural network: number of layers and neurons.

With a powerful graphical interface is easy and it is recommended to perform several models on the same input data in order to compare the forecasting results. Neural network architectures can be trained to predict the future values of the dependent variables. A *feed-forward neural network* consists of an input layer, one or several
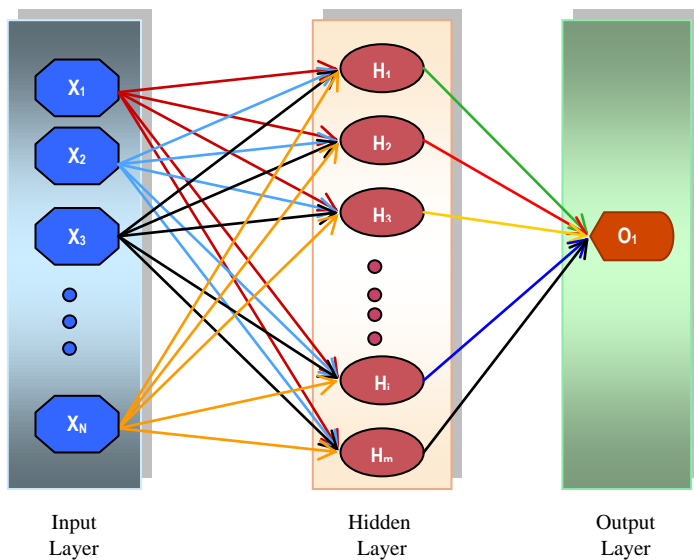
Fig. 1: Neural network architecture

hidden layers and an output layer. Another approach is known as the partially *recurrent neural network* that can learn sequences as time evolves and responds to the same input pattern differently at different times, depending on the previous input patterns [1]. So, the ANNs components are

- The network architecture: neurons, layers, inputs and outputs
- Describing inputs and outputs
- The training set and the validation dataset
- The training process
- The measure of the error.

As we can see in the fig. 1, a neural network is a system that connects an input dataset to a set of outputs in a non-linear mode. In a generally time-series context, the output is the value to be forecasted and the inputs are the previous-known values of the series and of other explanatory variables. The connections between inputs and outputs are made via one or more hidden layers of neurons, also called *nodes*. Choosing the architecture of a neural network implies to establish the number of layers, the number of neurons in each layer, and how the inputs, hidden layers and output(s) are connected [4]. The structure is the *feed-forward* type without feedback loops. A suitable architecture for a given problem has to be determined from the context, using some of the external considerations and the properties of the data. The model structure depends on its performance and the measure of error at each level is an indicator to choose an appropriate number of hidden layers.The architecture presented is for a typical neural network for time-series forecasting with *N inputs*,

one hidden layer of *m neurons*, and *one output* (the forecast).

In fig. 1, each input is connected to all neurons, and the neurons are connected to the output. The *strength* of each connection is measured by a parameter called a *weight*. There may be a large number of such parameters to estimate. A numerical value is calculated for each neuron at each time period, *t*, as follows.

The output variable, *y* at *t+1* moment depends on inputs until the chosen moment *t+1-i_x* and also on its values at previous moments (*o_x*). The model can be estimated as:

$$y(T)=f(x(T-i_1),x(T-i_2),...x(T-i_m),y(T-o_1),...y(T-o_m)) \qquad (1)$$

where y_j are the outputs, T = t+1 the time of estimation and x_i are the inputs.

The next step consists of choosing a nonlinear function, the *activation function*, for transforming the values of *y* into values for the neurons. The most important advantage of a neural network consists of the ability to represent nonlinear relationships and to *learn* from the previous behavior of the data being modeled [7][14].

In figure 2 is presented the graph of real function (*Real(x)*) and two models that approximate the function. The goal of the neural network is to create several models and select the function that correctly maps the input to the output using the training data („over fitting"). Two models, called *model1* and *model2* follow the *real* function. On training set (t <=100) *model2* approximate better the function, having a *bias* smaller than *model2*. The next step of the process refers to the comparison of the *test set* or *validation set* (the period between t=101 and t = 120) with the actual observations.

The final step is *forecasting stage* (the period between t = 121 and t = 170)*,* that means to compute the network response to new inputs, leading to a specific target output. The ANNs researchers describe the first part procedure as a *training algorithm* which *learns* by trial and error. Also, the new approach of forecasting is based on software applications for computing and testing the objective function until the error is minimized.

The stages for building an ANNs forecasting model

There are three main steps to build an ANNs forecasting:
- Detection of input patterns.
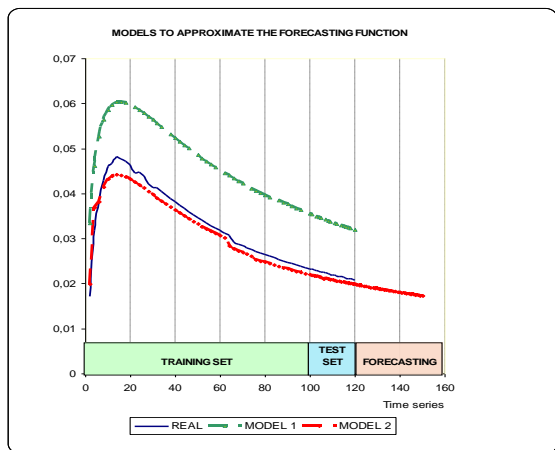- Determination of the number of neurons in hidden layers.

Fig.2: Modelling a nonlinear function

• Construction of the neural network forecasting.

"Time-series forecasting starts from the idea of extrapolation, in that it involves fitting a model to a set of data and then using that model outside the range of data to which it has been fitted. The usual method of analyzing such a series is to sample (or digitize) the series at equal intervals of time to give a discrete time series. Little or no information is lost by this process provided that the sampling interval is small enough" [3]. In some cases, the researchers use a univariate model, where a single variable is taken into account by the ANN such as the target indicator time series. So, we have a time series of daily, monthly or annual intervals, and an ANN with an input layer of N neurons and output layer with only one neuron. The input layer then holds the time series data points of T consecutive periods, and after the ANN is computed the output layer would hold the prediction for the (T+1)th period.

Usually is preferred a multivariate model in which is take into account several input variables and we must emphasize that some of them are more importants than others for the forecasting, and these will be preferred in the ANN model.

In the first stage, we will decide the input data, and how it should be split between training and test data. As for the second stage, choosing the number and size of the hidden layers in the ANNs, we will demonstrate that the optimal structure for a given problem optimal structure is based on trials and error calculated values [6][20]. The results of two different implementations are compared based on the value of Mean Squarred Error (MSE) [10][17]

$$ MSE = \frac{1}{N} \sum_{i=1}^{N} \left(\hat{Y_i} - Y_i \right)^2 $$

(2)

where $\hat{Y_i}$ is the vector of predictions and Y_i is the vector of true values.

Also, the accuracy may be evaluated taking into account the Root Mean Square Error (RMSE) [11][17]:

$$ RMSE = \sqrt{MSE\left(\hat{\theta}\right)} $$

(3)

where $\hat{\theta}$ is an estimator.

Modeling results will be specified tabular and graphical so that we may compare the accuracy of the representations.

Building a Forecast with GMDH Shell Software

The IT market records a large number of business intelligence and forecasting tools, the difference between them is often at the customization level and the taking over inputs. In manager opinions, some of the important criteria for choosing forecasting software are as follows.

• The market research in domain
• Costs of the license
• Forecast models and accuracy
• The range of supported input types
• Graphical user interface.

After an analyze of the IT market in domain of forecasting software offered as trial version and, in the context of research, we believe that GMDH Shell environment is appropriate due to more features: data acquisition, integration, neural network modeling, analysis and forecasting.

According to the documentation of the Group Method of Data Handling (GMDH): „GMDH Shell is an advanced but easy to use tool for predictive analytics and data mining, able to automatically detect usable data inside a file, transform data according to a problem type, drop irrelevant inputs and, finally, construct a set of predictive models at the base of optimal complexity detection and self-organization principals" [12].Analyzing the features of this forecasting software we made a summary of its strengths:

• Graphical User Interface for Windows is very friendly and consists of multiple panels: Data Manager (input dataset, target variables), Solver options, Simulation results.

• GMDH Shell accept the input dataset from XLS and CSV files, organized on columns and rows, some of them being the input variables and others the forecasting targets.

• GMDH Shell is able to solve different types of forecasting problems, especially Time-series forecasting which is a complex type of continuous value forecasting

- Applications of time-series forecasting include: financial management, evaluation of alternative economic strategies, production and capacity planning. To obtain a reliable model, time-series forecasting GMDH Shell treats and consider the validation dataset as important as that for training. *Time series preprocessor* panel allows the choice of core algorithms to learn from a training input data: neural networks or combinatorial type. We interested in neural networks algorithm, able to iteratively create layers of neurons with two or more inputs and to use a limited set of optimally neurons.

- Viewing and saving the results as graphical and tabular presentation of model performance and the importance of each indicator (as input variable) to the accuracy assessment for the modeled dataset. The current model for the target variable and also, other models of the same target are shown in visualization panels, using the Model browser panel [12].

In fig. 3 are indicated the steps to be followed to perform a forecast using the neural network algorithm of GMDH Shell.
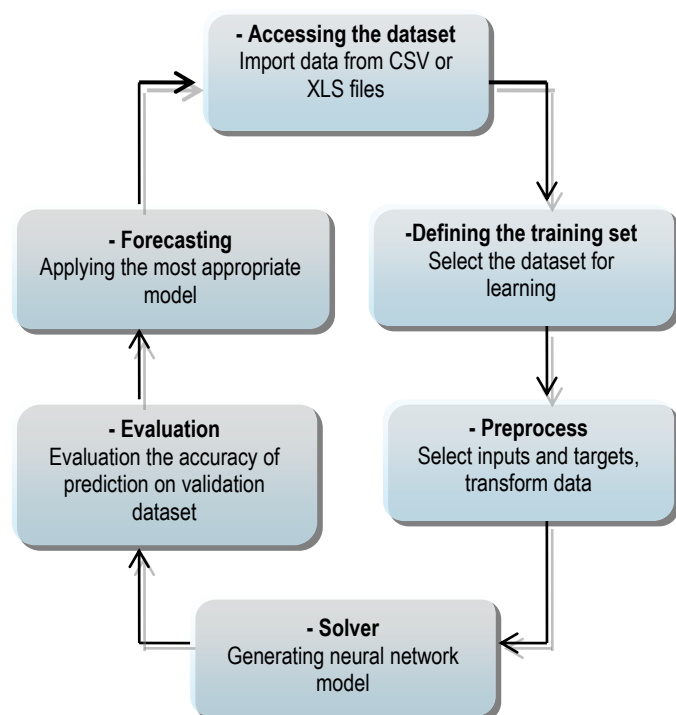

Fig. 3: Sequence of operations for performing a forecast using GMDH shell

From the software online documentation results several operating principles of the forecast algorithms based on neural network [12].

- Algorithms focuses on the two-level validation approach, the second validation level, called *hold-out sample*, is not implicated in estimation of model structure, but it is used to validate the modeling attempt, the performance of processed predictions. This second validation may alert about over-fitting or about low quality model.

- The model complexity can be increased by using built-in validation strategies in order to achieve forecast accuracy. The main idea is to create layers of neurons with two or more inputs, saving a set of neurons that will contribute to the next layer. So, every new layer is based-on two or more neurons from previous layers.

- The process of creating layers ending in one of the following cases:

▪ The most recent layer did not provide a better accuracy than previous layer;

▪ The testing error was reduced by less than 1%;

▪ The number of layers has reached the configuration limit.

Study Case: A Financial Forecasting for OMV Petrom SA Company

Our goal was to obtain a forecasting of financial indicators for 2012 for OMV PETROM S.A. Company. In order to do this we applied various forecasting models using the company's consolidated financial statements over the period 2005-2011. Based on the partial data provided by the company in the first two semesters we also made an assessment of the accuracy of predictions, and we analyzed the mismatch causes.

Starting from 2004, OMV Aktiengesellschaft implemented a coherent development strategy that made from OMV PETROM S.A. one of the largest companies in Southern and Eastern Europe. OMV Aktiengesellschaft is the major shareholder of the OMV PETROM S.A. with 51.01% of the shares. The other shareholders are: the Ministry of Economy in Romania (20.64% of shares), Property Fund SA (20.11% of the shares), the European Bank for Reconstruction and Development (2.03% of shares) and some small individuals and businesses in Romania and abroad.

The company major activities such as: Gas and Power, Exploration and Production, Refining and Marketing, along with an investment of over EUR 7.7 billion in the last seven years in a process of modernization and efficiency, makes from OMV

PETROM S.A. the largest oil group in South East Europe. OMV PETROM Marketing performs the company's oil trading activity in Romania and also a newer activity on the electricity area by developing a gas power plant of 860 MW at Brazi and began commercial operations in Dorobanțu wind farm with a capacity of 45 MW. Beside Romania, where exploits oil and gas proved

reserves estimated at 786 million barrel, the Group activates also in Kazakhstan with a narrower activity in the same area. OMV PETROM operates on the petroleum products distribution market under the brands PETROM

and OMV in the following countries: Romania, Bulgaria, Serbia and Moldova.The increasing interest of investors for the company is justified by the improvement of the following indicators during the last four years.

Table 1: The improvement of financial indicators during 2008-2011 [2]

Year	2008	2009	2010	2011
Number of shares, (million)	56.644	56.644	56.644	56.644
Market capitalization (million Euros)	2.609	3.356	4.429	3.803
Dividend Yield (%)	-	-	5,2	10,7
Rate of profit distribution (%)	-	-	46	47

The effect of the previous year's trading on the business is reflected on the consolidated financial statements at the end of the financial year (fig. 4 - Evolution of Gross profit, Turnover and Expenses during 2005-2011).
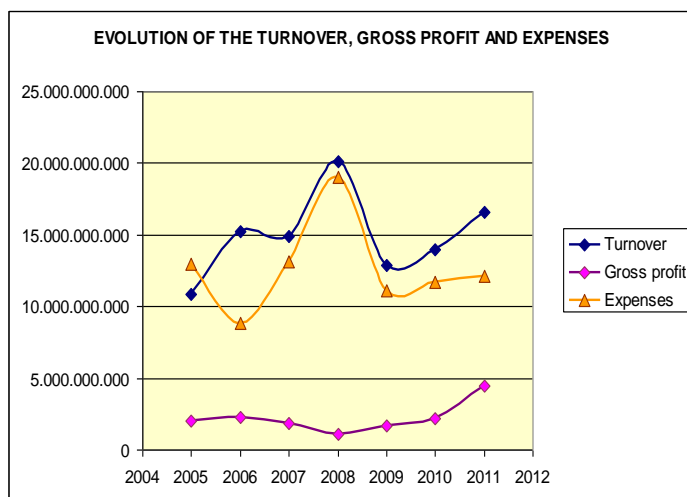

Fig. 4: Evolution of gross profit, turnover and expenses during 2005-2011

Key performance indicators highlighted in a consolidated balance sheet demonstrate:1.

Return on Equity

Return on equity reflects the efficiency of use shareholders invested capital RE = Net Profit/Equity x 100

Financial Autonomy Rate

Financial autonomy rate express the company's financial independence. The increasing of the company equity share in its permanent capital

has benefic effects on the total financial autonomy.
FAR = Equity/Permanent capital x100
The company's total financial autonomy increased in 2011 compared to 2006.

The General Solvency Ratio

Financial autonomy rate expresses the extent the assets of the society contribute to its forward total debt.Overall solvency rate –express the level in which the assets of the company contribute to its total debt financing (fig. 5).
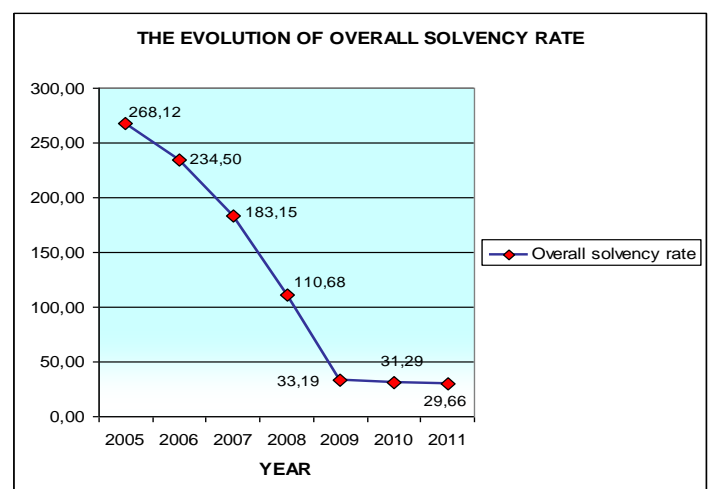OSR = Total assets/Total liabilities x 100

Fig. 5: Evolution of overall solvency rate during 2005-2011

Even if during the period 2006-2009, the company's debt could be settled using the available assets, after 2010 the increasing of the current liabilities deteriorated the company's general creditworthiness.

Rate of Economic Return

Rate of economic return Express the efficiency of assets use, namely their contribution to achieving results.
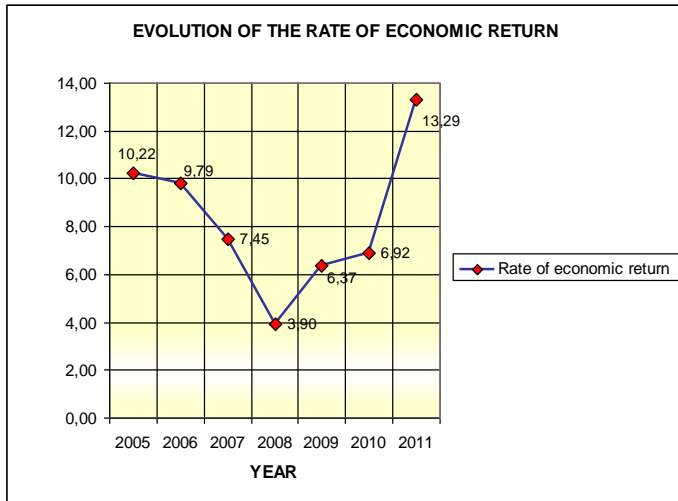RER = Gross profit/Total assets x 100

Fig. 6: Evolution of rate of economic return during 2005-2011

Company economic profitability fell in the mentioned period with a minimum of 3.9% in 2009 (fig. 6).This section will explain how to prepare data, choose the model, and make the configuration in

GDHW Shell in order to obtain a forecasting for two key performance indicators on 2012: Overall solvency rate and Rate of economic return. The sequences of actions that a manager must follow for building a forecasting using GMDH Shell begin with the *import* of data from an Excel or CSV file (Fig. 7). First example consider that the target variable is Overall solvency rate, and the input variables are the indicators from the OSR formula (total assets, total liabilities), and also others that may affect the target (Long term liabilities, Stocks).

The model template choosen is GMDH-type neural networks and related to the model, we must refer to the *Configuration Preprocesing* for Time-series modeling options: window size, forecast horizon, perform *n* simulations.

The *Solver* panel provides the most important options, related to the chosen algorithm (fig. 8):
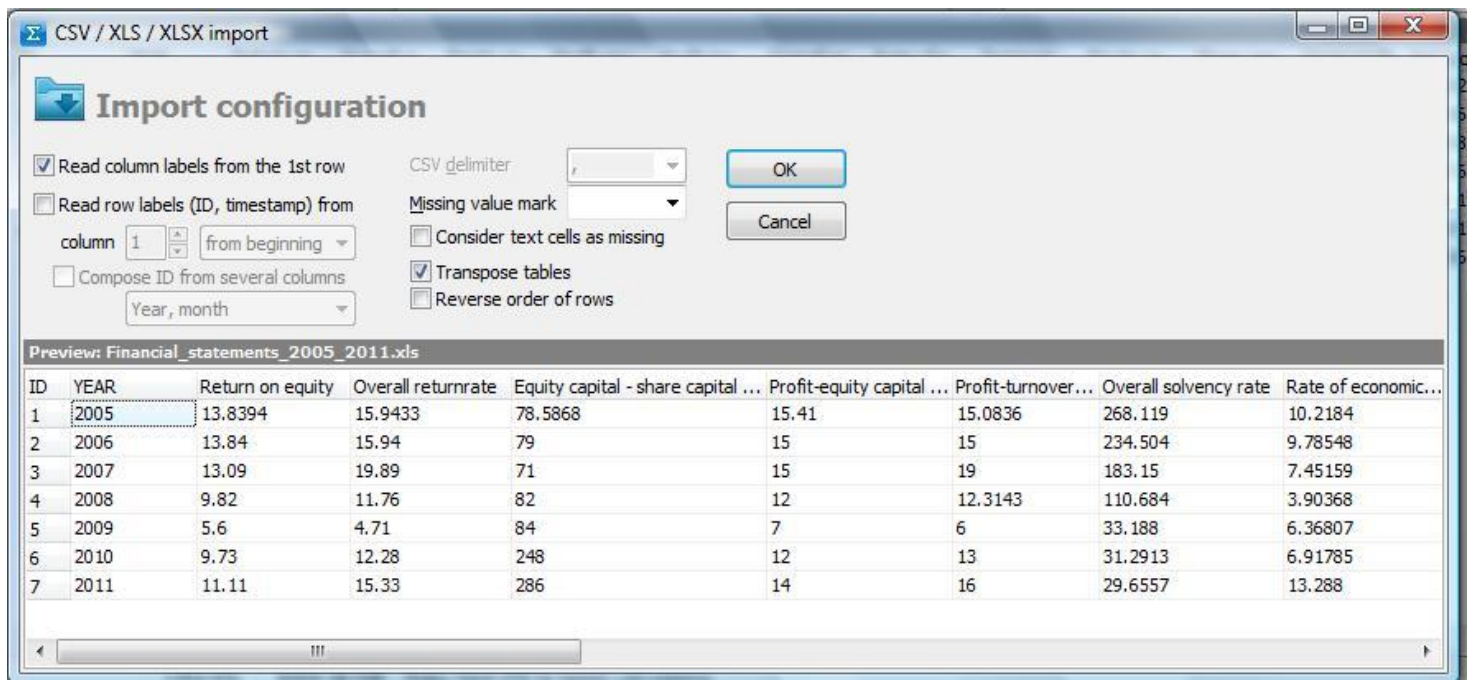

Fig. 7: Import of dataset from an excel file

· Validation strategy – Training/testing, that splits dataset into two parts, one for training and the other for model validation;
· Train/test ratio – from window size (6 values availables), we consider that 5 are necessary for detecting the model pattern and one value for testing it;
· Validation criterion – Mean Absolute Error (MSA) or Mean Squared Error (MSE) will be the measure of the model performance and we change the input variables and the configuration until this indicator will be smaller than 1%;

· Core algorithm – Neural type, that iteratively creates layers of neurons with two or more inputs following a neuron function (linear, polynomial and quadratic polynomial).

The Simulation results panel has many components: Plot, Table, Importance and Raw table. In figure 8 is highlighted the Plot tab, which presents a graphical estimation of the forecasting: blue curve with red addition (predicted for next time horizon chosen) that
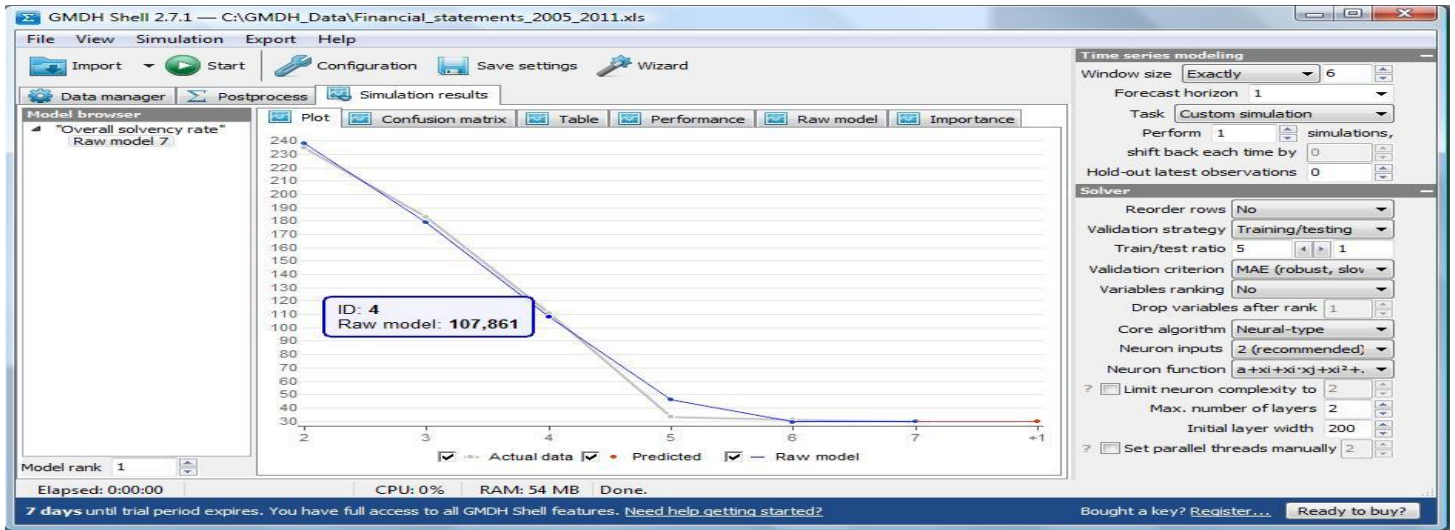
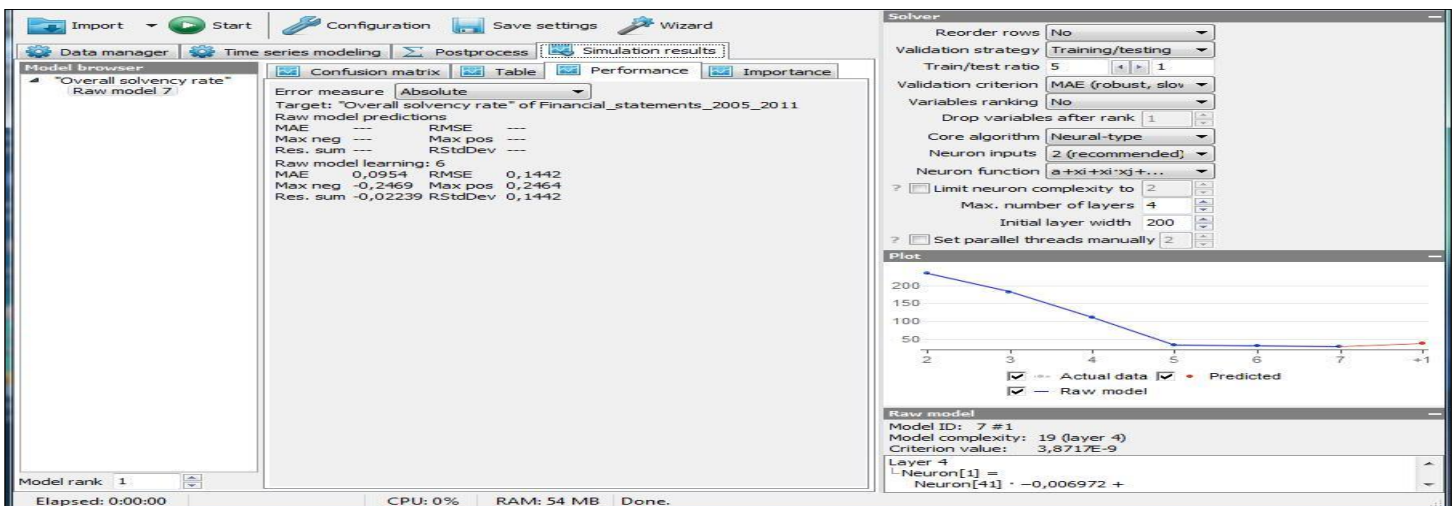**Fig. 8: Time series modeling and Solver configuration that produce the correspondent simulation results**

Fig. 9: The performance tab of simulation results panel
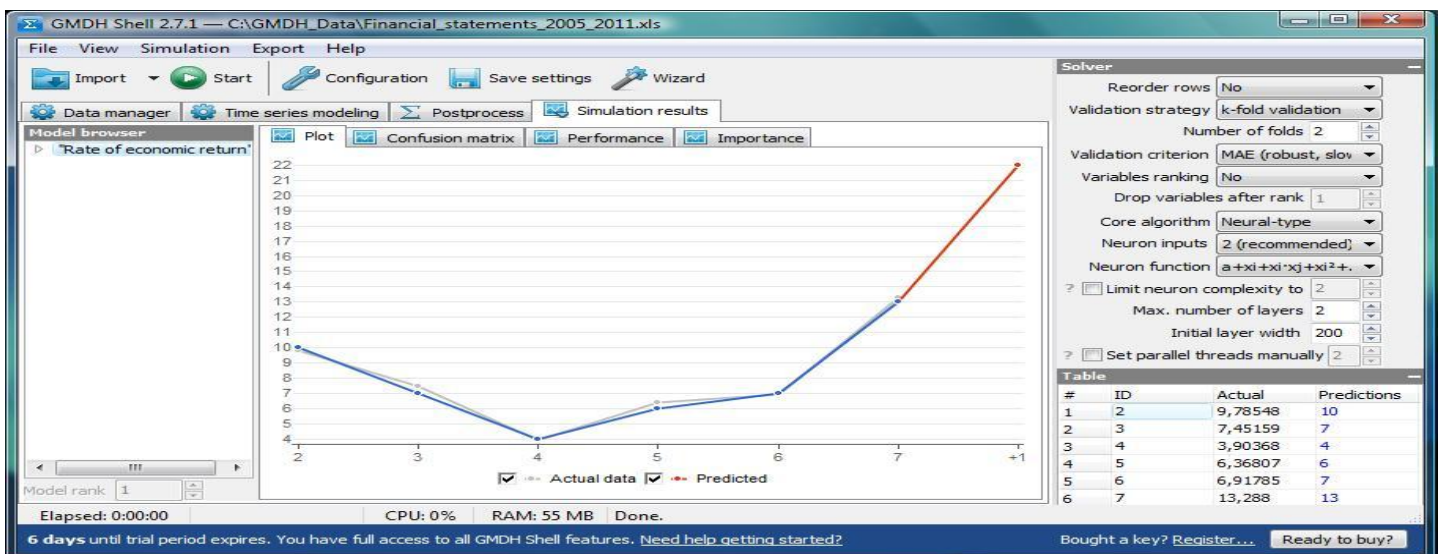

Fig.10: The performance tab of simulation results panel using rate of economic return

marks model forecast, gray curve for actual data [2].From Table tab results that the predicted value for OSR is 39, following the trend of the period 2009-2011.Fig.9 shows an appropriate alternative of the neural network for modeling the Overall solvency

rate, based on neural-type algorithm, with 4 layers and a polynomial neuron function. Thus, it was obtained a higher forecasting accuracy of the model, defined by the smaller value of Mean Absolute Error (MAE) from the rank: 0,094. The results demonstrate that the frame size has an

important effect on the quality of a neural network based forecaster [5]. From this experiment it can be seen that optimal performance is obtained at the correct window dimension and training/test ratio.Also, we applied a short-term forecasting, taking account of manager expectations and ensuring a minimum mean square error. We used a time series consisting of discrete values, but there are opinions according to which it is better to use a median distribution, that stops extreme values and is more coherent [8]. Following the same sequence of operations, we will obtain other key performance indicators, such as: Rate of Economic return (Fig. 10).After several attempts of simulation using different models, was defined the pattern closest to the reality, that offered the predicted value 21, keeping the upward trend.

Conclusion

In the current context of a deep and prolonged economic crisis, forecasting has become an effective tool, decisive for managers of large companies. To obtain a degree as higher as it can

of accuracy of the model, it is recommended a sample (window) as larger as it can be of the input dataset, and also, a comparative analysis of different types of models. Featuring financial consolidate statements, the managers may conceive forecasts for key financial indicators of the companies and may realize the estimates correlating.

Obviously, the level of confidence of these predictions depends on the software knowledge and its limitations, requires testing several models on the same input dataset in order to reduce the inherent risks of certain variants approach. In our case study, the forecast accuracy is affected by the reduced set of input data (window size is 7, representing the period from 2005 to 2011). Also, we did not take into account all factors (micro and macroeconomic) that can influence the OSR indicator. Forecasting financial indicators of a company becomes a decision support system, allowing the manager to analyze and monitor past and current performance and to decide the direction in which the company will evolve in the future.

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