# PREDICTION OF IMKB SECTOR INDICES

# BY USING ARTIFICIAL NEURAL NETWORKS

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# PREDICTION OF IMKB SECTOR INDICES

# BY USING ARTIFICIAL NEURAL NETWORKS

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Thesis Abstract

Ömer Faruk Çevik, "Prediction of IMKB Sector indices by Using Artificial Neural Networks"

Stock market predictions play an important role for making right investment decisions. Investors can gain very high returns in short time in stock exchanges if correct stocks are chosen or they can lose their earning. Researchers are interested in stock markets for decades. Today, stock market topics are still examined by many scholars, since the factors determining the market conditions are changing continuously and none of the studies provide a complete and accurate solution for stock exchange direction.

Academicians build many studies for modeling stock market behaviors and making different type of predictions such as selecting stocks with high rate of returns for portfolios, determining buy-sell point for indices or stocks, simulating economical crises time for providing alarm signals if crisis situations are likely, providing up or down signals for indices and etcetera.

This study's aim is to analyze the behaviors of sector indices of Istanbul Stock Exchange like XTRZM (Tourism companies), XKMY (Chemical companies) and make prediction for those sub-indices instead of making predictions for overall İstanbul Menkul Kıymetler Borsası (IMKB) index. Artificial neural network approach which uses past data of sub-indices will be used to predict sector indices of IMKB. Stocks which constitute the sector index will be found and the stocks' past data will be analyzed by artificial neural network approach.

Tez Özeti

Ömer Faruk Çevik, “IMKB Sektör Endekslerinin Yapay Sinir Ağları Yöntemi ile Tahmin Edilmesi”

Hisse senedi piyasaları tahmini yapmak doğru yatırım kararlarının verilmesinde önemli bir yere sahiptir. Doğru yatırım tercihi yapıldığında yatırımcılar borsa yatırımlarından kısa zamanda yüksek oranda kazanç sağlayabilmekte veya yine kısa zamanda yüksek oranlarda kayıp yaşayabilmektedirler. Borsa tahminleri çalışmaları yıllardır araştırmacılar tarafından gerçekleştirilmektedir. Bugün yine birçok borsa konusu akademisyenler tarafından araştırılmaktadır çünkü borsanın yönünü belirleyen etmenler sürekli olarak değişmekte ve yapılan çalışmalar borsa ile ilgili gerçeğe yakın tahminler üretmekte zorlanmaktadır.

Akademisyenler tarafından, borsada yüksek kazanç getirebilecek hisselerden portföy yapılması, borsa artma veya azalma yönünün belirlenmesi, hisse senetleri veya endeksler için alış-satış noktalarının belirlenmesi ve ekonomik krizlerin tahminlemesinde bulunulması gibi alanlar ile ilgili bir çok çalışma gerçekleştirilmiştir.

Bu çalışmanın amacı İstanbul Menkul Kıymetler Borsası’nda (IMKB) bulunan alt endeksler olan XTRZM – Turizm şirketleri endeksi, XKMY – Kimya şirketleri endeksi gibi endekslerin tahminlemesini yapmaktır. Endeksleri oluşturan hisselerin tarihsel verisi yapay sinir ağlarında kullanılarak endeksler için tahmin üretilecektir. Sektör endeksleri içerisinden yükseliş veya düşüş eğilimindeki sektörlerin bulunması çalışmaları gerçekleştirilecektir.

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# CHAPTER I

# INTRODUCTION

Globalization of the world economy allowed free flow of capital among countries for investment in financial markets. Millions of investors make transactions in the finance markets every day. Either individual investors, who are called small investors, make investment with their own capital, or professional fund managers of banks and other financial institutions who decide to invest or sell up to billions of United States dollars.

Prediction of stock exchange performance is critical for making investment decisions. Portfolios of investors are allocated according to expectations on investment tools like stocks, bonds, commodities and exchanges. A variety of software is used to help investors in different ways. Software can be used to select stocks for portfolios, to determine if the stock exchange market will be faced with an economic crisis, to provide buy or sell signals and so on.

Artificial Neural Networks (ANNs) are used in stock exchange software widely because artificial neural networks are applicable to multivariate non-linear problems. Also there is no need to assume an underlying data distribution such as normal distribution which is usually done in statistical modeling and like human brains ANNs learn patterns from past experiences, detect hidden relationships between input and output variables and in similar situations they detect the analogous.

There are many studies performed by researchers for IMKB. Most of the studies were performed to predict overall IMKB index or big companies indexes. But there is not a study in literature about sector indices of IMKB, like tourism, chemistry or banking index.

This study’s aim is to predict sub-indices in IMKB by using past data. Trading information like previous séance’s trading volume, number of contracts, maximum, minimum and average values of stocks are used in neural networks for forecasting indices in IMKB. So that it is aimed to find out if it is a better way to predict sector instead of all index or individual stocks.

In Chapter I, study is explained briefly and motivation for the study is made clear. In Chapter II, definitions and basic terms about stock markets are explained and then literature survey is given which contains past studies about neural networks and neural network applications in finance.  Chapter III will construct a model which will detail data cleaning, data transformation and then using data in neural networks. Chapter IV will demonstrate results and discussion and finally a brief conclusion is given in Chapter V.

Motivation

Investment tolls provide huge earnings when right decision is made or investing in an investment tool can cause large losses in short time especially in volatile periods. IMKB, for example, increased from 21.228 points to 59.334 points (November 2008 - April 2010) which brought 179 % net increase in terms of Turkish Liras. However before that boom period, IMKB decreased from 58.000 to 22.000 (62 % loss) in 14 months. 3 years performance of IMKB between 2007 and 2010 can be seen in Figure 1.

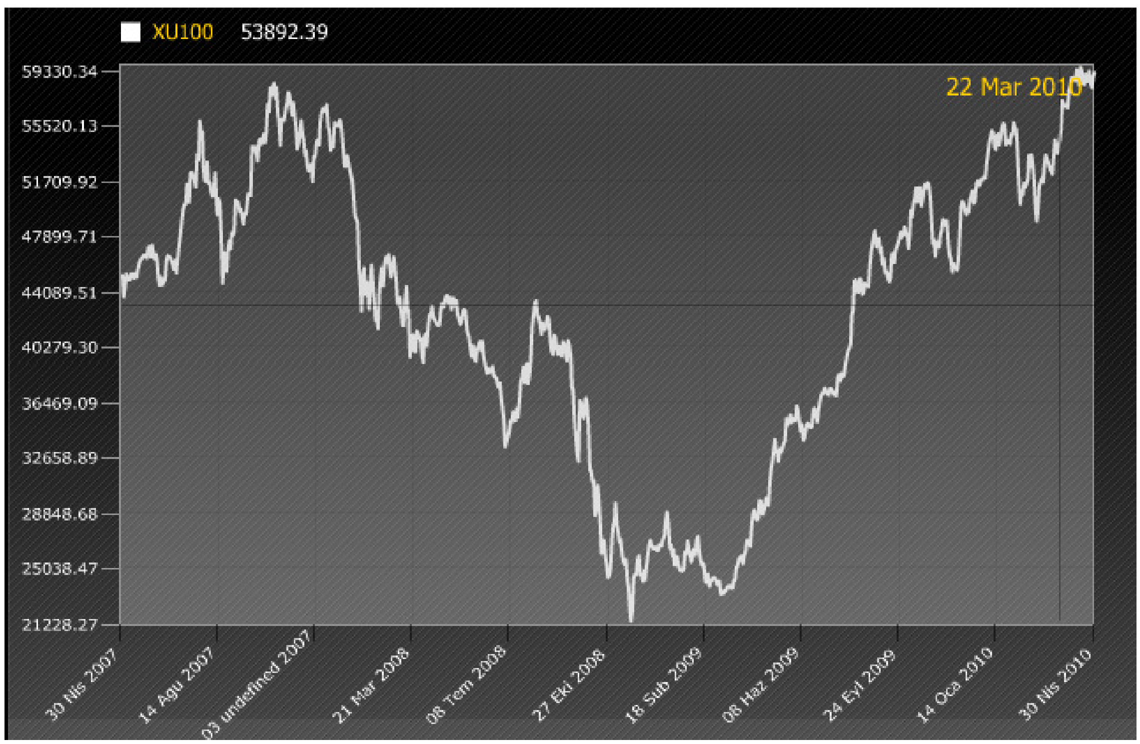


Figure 1: 3 years performance of IMKB 100

What is more, banking index of IMBK had increased from 42.000 to 137.300 which indicated 226 % profits in the same time interval (Figure 2).

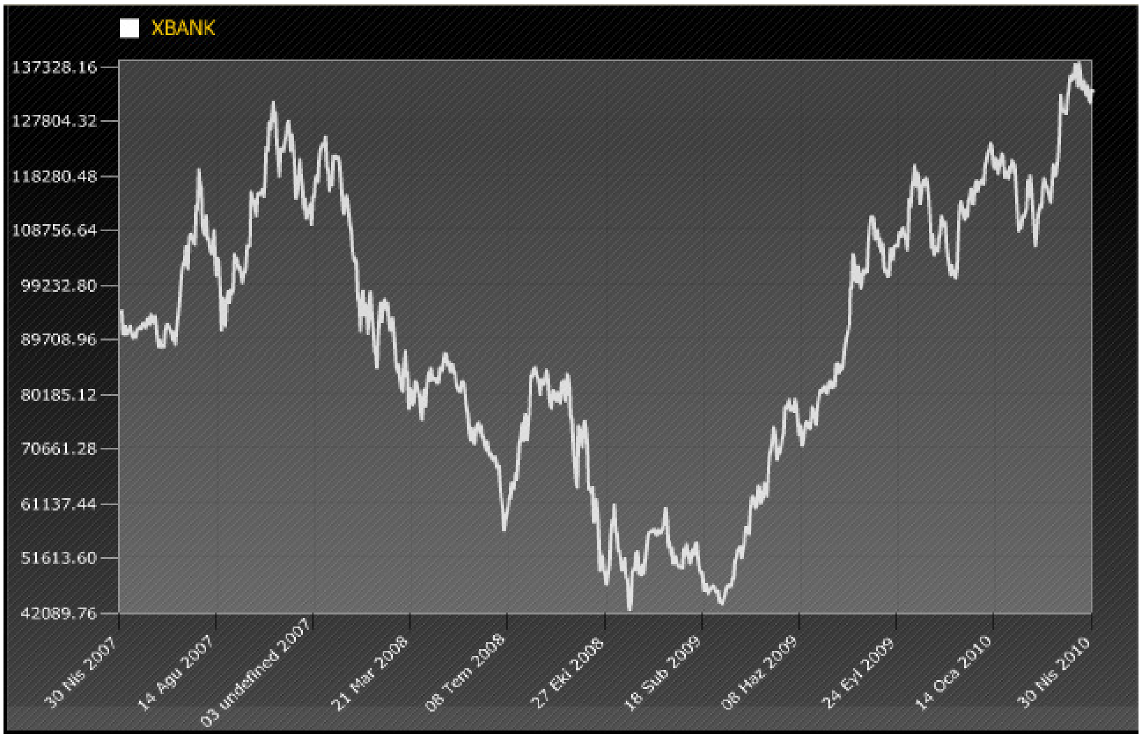


Figure 2: 3 years performance of XBANK, banking index of IMKB

So, generating signals for sectors instead of overall stock index can provide better performance to users of the system both in boom and down periods. Sectors which are expected to increase more than other indices are candidates for investment opportunities and sectors which are not potentially profitable than other indices might not be included in portfolios. In this study neural network training will be performed for prediction of sub-indices of IMKB. Stocks which belong to selected sector index are found and their past data will be used to make forecasts.

# CHAPTER II

# LITERATURE REVIEW

Firstly, basic definitions and stock exchange terms explanations will be introduced in definitions part. Then studies which use neural networks in financial applications will take a part in literature survey.

## Definitions

It is better to familiarize with terms related with finance, stock exchange markets and investment environment to understand the study better. Financial terms will be explained briefly in encyclopedic terms.

### The Market

A market is an arrangement that allows buyers and sellers to exchange things. The concept of a market is any structure that allows buyers and sellers to exchange any type of goods, services and information. The exchange of goods or services for money is a transaction. Market participants consist of all the buyers and sellers of a good who influence its price. Markets vary in types of goods and services traded. Some examples include local farmers' markets held in town squares or parking lots, shopping centers and shopping malls, international currency and commodity markets, legally created markets such as for pollution permits, and illegal markets such as the market for illicit drugs (Wiki Market, 2010).

## The Financial Market

The material wealth of a society is determined by the goods and services provided to its members. This productive capability is a function of real assets of the economy: the land, buildings, knowledge, and machines that used to produce goods. Financial assets define the allocation of income and wealth among investors. When real assets used by a firm ultimately generate income, the income is allocated to investors according to their ownership of financial assets, or securities, issued by the firm (Bodie et al., 2006).

## Investment

In encyclopedic definition, investment is the commitment of money or capital to purchase financial instruments or other assets in order to gain profitable returns in form of interest, income, or appreciation of the value of the instrument. When we analyze people's expectations from an investment, it is derived that a financial instrument is bought by capital holders for a certain period of time to save money in addition to the expectation from that financial instrument bringing additional increase in value that is called profit. Simply, people invest to build wealth for their future (Wiki Investment, 2010).

## Financial Instruments

Capital owners or money holders can invest a variety of investment tools. Those investment instruments constitute portfolios of investors according to investor's expectations from those instruments. Financial instruments; the money market, the bond market, derivative market and stock market are defined below (Bodie et al., 2006):

## The Money Market

Money markets offer investors to lend money for short-term, usually less than one year, for predetermined interest. Money market consists of treasury bills (T-bills), certificate of deposit (CD), commercial paper, banker's acceptance, Eurodollars and repos. Those instruments are risk-free, the income is known, extraordinarily safe, but offer significantly low return compared to other investment tools (Investpedia Money Market, 2010).

## The Bond Market

A bond is simply a type of loan taken out by companies. Investors loan a company money when they buy its bonds. In exchange, the company pays an interest "coupon" at predetermined intervals (usually annually or semiannually) and returns the principal on the maturity date, ending the loan (Investpedia Bond Market, 2010).

## Derivative Markets

Derivative is a security that its price is dependent upon or derived from one or more underlying assets. The derivative itself is merely a contract between two or more parties. Its value is determined by fluctuations in the underlying asset. The most common underlying assets include stocks, bonds, commodities, currencies, interest rates and market indices. Most derivatives are characterized by high leverage (Investpedia DerivativeMarket, 2010).

## Stock Market Indices

Common stock, also known as equity, represents ownership shares in cooperation. Stocks of a company are issued to the stock exchange market by the firm with a face value, and then stocks are tradable among investors in the stock exchange market. Value of a stock can change according to supply-demand rule. If total demand amount for a stock is higher than total selling amount, price of the stock tends to increase. When sellers are more than buyers, stock price begins to decline. The factors effecting investors' buying or selling decision will be analyzed in next section.

A stock market index is a method of measuring a section of the stock market. A national index represents performance of the stock market of a given nation. National indices are mostly represented by biggest companies traded in the market such as IMKB 100, American S&P 500, the Japanese Nikkei 225, and the British FTSE 100. Also there are indices covering stocks in the same type of industry like XTRZM represents overall performance of tourism companies, XBANK represents banking companies in IMKB. Similarly Dow Jones Industrial Average and Dow Jones Transportation Average are represented in US market. Also there are global and regional indices like The S&P Global 100 measures the performance of 100 multi-national companies and FTSE Eurotop 100 - 100 most highly capitalized blue chip companies in Europe. Market indices are calculated according to weighted average method. Each stock's value change is multiplied by a weight and the results are summed to determine index value.

Weight of a stock is determined according to market value of that stock (Wiki Stock Market Indices, 2010; Bodie et al., 2006).

In IMKB, there are sector based, region based and company size based indices. Sector and size based indices are given in Table 1 (Oyak Yatırım, 2010).

Table 1: IMKB Sector Indices

| Index Code | Index Name |
|---|---|
| XUTUM | National Index |
| XU100 | IMKB compound |
| XU50 | National Big 50 Companies |
| XU30 | National Big 30 Companies |
| XUMAL | National Financial Index |
| XUSIN | National Industry Index |
| XBANK | Banking Index |
| XBN10 | Top 10 Banks Index |
| XKAGT | Forest and Paper Index |
| XKURY | Corporate Management |
| XHOLD | Holding and Investment |
| XUHIZ | Service Index |
| XKMY | Chemistry, OIL and Plastic Index |
| XMANA | Metal Main Index |
| XMESY | Metal Goods and Machinery Index |
| XULAS | Transportation Index |
| XGMYO | Real estate Investment Corporation Index |
| XTAST | Stone and land Index |
| XUTEK | Technology Index |
| XGIDA | Food and Drink Index |
| XILTM | Communication Index |
| XSGRT | Insurance Index |
| XBLSM | Informatics Index |

| | |
|---|---|
| XYORT | IMKB Investment corporation |
| XTEKS | Textile and leather |
| XELKT | Electricity Index |
| XTCRT | Trade Index |
| XFINK | Financial Factoring Index |
| XTRZM | Tourism Index |
| XSVMN | Defense Index |
| XSPOR | Sport Index |

Sectors' stock numbers vary. There are small indices like sport index which have only 4 stocks and indices which contain tens of stocks like chemistry index with 20 stocks. Regional or city based indices are given in Table 2.

Table 2: City Indices of IMKB

| Index Code | Index Name |
|---|---|
| XSANK | Ankara Index |
| XSIZM | Izmir Index |
| XSBUR | Bursa Index |
| XSANT | Antalya Index |
| XSADA | Adana Index |
| XSTKR | Tekirdağ Index |

In this study some of the sector indices will be selected randomly and they will be forecasted using ANN. City indices are not used.

## Stock Market Hypotheses

Badawy et al. (2005) indicated that there are three views regarding stock market prediction; efficient market hypothesis, fundamental analysis and technical analysis. Stock market direction forecasting has become topic of many academic studies for decades in guidance of those three basic views. Academicians developed different models for a variety of purposes. Some studies tried to provide an alarm system for economic crisis, some studies performed stock market direction prediction, some of the studies' aim was to constitute portfolios with stocks which are expected to increase and other studies tried to find buy and sell points for indices or stocks and many others. Still stock market studies are performed by researchers since none of the past studies provide an accurate solution for stock market prediction.

According to random walk hypothesis and efficient market hypothesis (Taylor, 1986), investors cannot determine future trend of stocks by studying past and present data and cannot achieve more than average market return given the information publicly available at the time the investment is made. The second view is that of fundamental analysis. According to fundamental analysis, sector specific developments or changes, various macroeconomic factors, financial statements (cash flows, profitability and etcetera), management and competitive advantages of company can explain the changes in stock prices. According to Tan (1997), fundamental analysis' factors determine the actual price of a stock. If the price is undervalued by the market, investing in that stock will bring profit or vice versa. Tan (1997) also indicated that fundamental analysis is suitable for long term investments.  Technical analysis represents the other view for market price prediction. Technical analysis believes that there are recurring patterns in stock markets, whether for overall stock market and for individual stocks in the market, and those trends can be identified and can be caught by examining certain statistical indicators. Analysts use number of statistical parameters called technical indicators such as volume information, moving average of index in the last 6 months, maximum value of index in one year and charting patterns from historical data. Murphy (1986) summarized technical analysis in three bases; stock price reflects all related information of stock, prices move in trends and history repeats itself. So, technical analysis can explain price changes by regarding previous trend patterns.

## Stock Market Prediction Methods

Chang et al. (2009) indicated that there are three fundamental methods for stock prediction models. Time series forecasting, case based reasoning and machine learning methods. In recent studies, hybrid systems are built which uses selected methods together. Those hybrid systems can use one of the methods more than one time.

### Time Series Forecasting

Time series forecasting usually uses statistical and linear methods with past data for predicting future values. Time series analysis performs better than other models for the forecasting models with trendy and seasonal features like ice cream consumption, number of tourist visits to a hotel in summer. A fixed interval trend removal approach is used to successfully forecast the electricity demand (Infield & Hill, 1998). There are a variety of models used in time series: the autoregressive (AR) models, the integrated (I) models, the moving average (MA) models, exponential smoothing, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA) models, the autoregressive fractionally integrated moving average (ARFIMA) model, autoregressive conditional heteroskedasticity (ARCH) models and so on (Wiki Time Series, 2010).

Regarding the stock market prediction, investors believe that the future behavior of the stock markets are based at least in part on present and past events and data (Tan et al., 2005). Financial time-series has high volatility and changes with time. In addition, movements of stock markets are affected by many macro-economical factors such as political events, firms' policies, general economic conditions, investors' expectations, institutional investors' choices, movement of other stock market, psychology of investors (Wang, 2002). Risk factors for markets are identified in Fama and French (1993) as an overall market factor, factors related to firm size and book-to-market equity which seems to explain the average returns on stocks and bonds. Financial time-series is one of the most "noisiest" and "non-stationary" signals present and hence difficult to forecast (Oh & Kim, 2002). Tunçel (2009) analyzed beta coefficient stability of 189 stocks in Istanbul Stock Exchange (ISE) for periods of 4 and 8 years. Both 4 and 8 year intervals provided the same stability and it is found that the characteristics of intervals, company profiles and investor profiles have affects on beta values of stocks rather than time interval extend.

## Case Based Reasoning (CBR)

Case based reasoning solves new problems by adopting previously successful solutions to the newly faced problems (Aamodt and Plaza, 1994). In case based reasoning, it is very critical to find out similar cases from an archive. The cases archive's indexing method should be organized in a way that it provides efficiency in inserting new cases, searches in past cases and retrieving old cases and matching it with the new situation becomes fast and reliable (Kolodner, 1993). There are 4 CBR steps:

1. Retrieve: Finding most identical case from previous experiences.

2. Reuse: Stating which parts of retrieved case is used for which part of solution. Combining information from retrieved cases to solve new problem.
3. Revise: Checking if provided solution from reuse is applicable. If so, process is forwarded to the last phase.
4. Retain: Process of a new case insert to the cases archive and making necessary updates in the database if solution is successful.

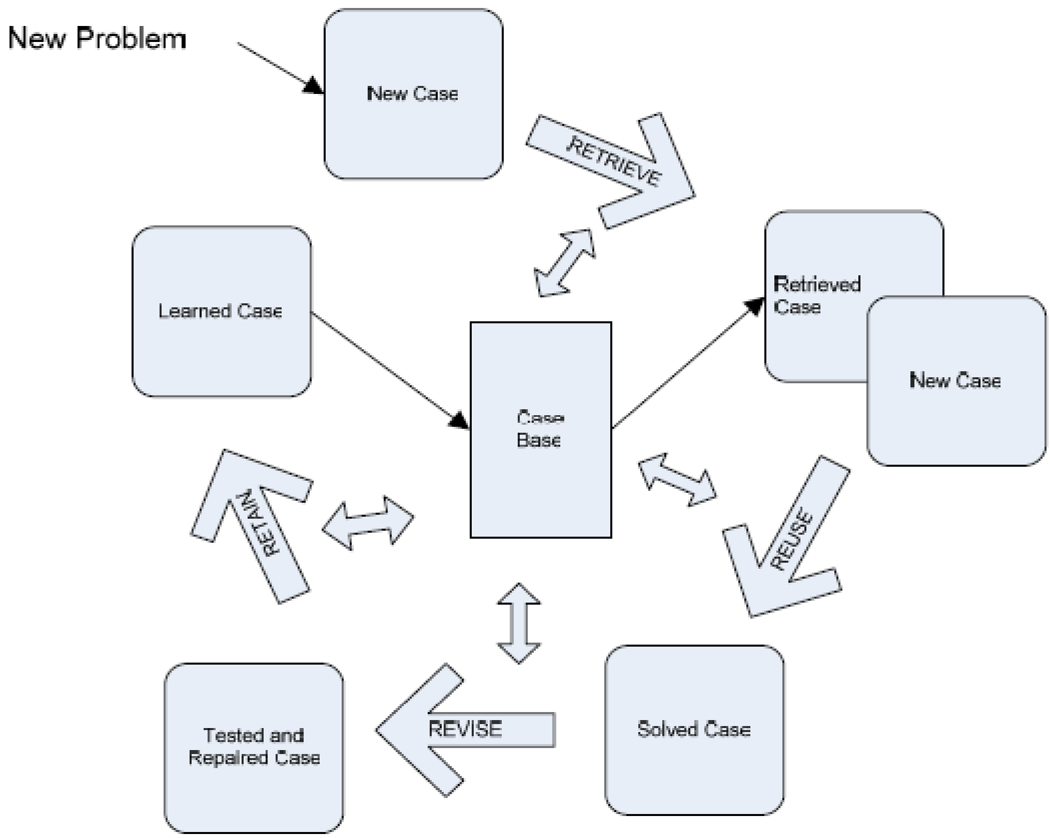


Figure 3: CBR Cycle
(Aamond and Plaza, 1994)

After finding the most similar problem, researchers use different methods according to problem definition. Chang et al. (2009) used case based reasoning as a verification tool after finding potentially profitable stocks with back propagation. A software using CBR to provide decision support to construction projects is built by Li (1996). This model is applied to a computer software called MEDIATOR which utilizes past cases of construction and infrastructure projects as a basis for handling new problems.

## Artificial Neural Networks

Artificial neural networks originally inspired from basic biological neural systems. The human brain particularly, is composed of a number of interconnected simple processing elements called neurons or nodes. Each node receives an input signal which is the total ‘‘information’’ from other nodes or external stimuli, processes it locally through an activation or transfer function and produces a transformed output signal to other nodes or external outputs ( Zhang et al., 1998). Artificial neural networks have emerged as a powerful forecasting tool and one major application area of ANNs is forecasting (Sharda, 1994). ANNs are data-driven self adaptive methods that do not need to assume a statistical data distribution. ANNs detect the hidden relationships within input data, even if the underlying relationships are unknown or hard to describe, and perform tasks like pattern recognition, classification, evaluation, modeling, prediction and control (Lawrence and Andriola, 1992). Thus ANNs are applicable for problems where solutions require knowledge that is difficult to specify but for which there are enough data or observations (Ripley, 1993). Also ANNs can generalize. After learning the data presented to them (a sample), ANNs can often correctly infer the unseen part of a population even if the sample data contain noisy information. As forecasting is performed via prediction of future behavior (the unseen part) from examples of past behavior, forecasting become an ideal application of ANNs in theory ( Zhang et al., 1998). As final advantage, ANNs are capable of performing nonlinear modeling without a prior knowledge about the relationships between input and output variables. In other words, ANNs can solve nonlinear and complex iterations in multiple layers. Since most of the real world systems are nonlinear (Granger, 1993) and the formulation of a nonlinear model to a data set is very difficult because of many possible nonlinear patterns, ANNs have superiority in forecasting over statistical methods.

An artificial neural network is typically composed of several layers of many computing elements called nodes. Artificial neural networks are characterized by the network architecture, that is, the number of layers, the number of nodes in each layer and how the nodes are connected (Chokri and Abdelwahed, 2003). The first layer is called the input layer where external information is received. The input layer is composed of pieces of input data which describe the situation being studied. Depending on the case examined, inputs are selected and given to the first layer. Kim et al. (2004) used 4 inputs for recognizing sudden price changes which might be economic alarm in Korean Stock Price Index. Daily rise and fall rate of index, 10 day moving average rate of index, 10 day moving variance of index and moving variance ratio of Korean index are used in input layer. The values given together for input nodes represent one pattern to be studied by the network. These node values provide the initial signals to the neural network. Since neural networks do not require linearity, qualitative data like month of year, day of week and nationality of company owner can be used as inputs.

Each computational unit (see Figure 4) has a set of input connections that receive signals from other computational units and a bias adjustment, a set of weights for each input connection and bias adjustment, and a transfer function (y value in Figure 4) that transforms the sum of the weighted inputs and bias to decide the value of the output from the computational unit. The sum value for the computational unit (node) is the linear combination of all signals from each connection (xi) times the value of the connection weight between node j and connection i (since there is one node in Figure 4 there is not a j value and Wji = Wi). If the transfer function applied in equation is linear, then the computational unit resembles the multiple regression models. If the transfer function applied in equation is the sigmoid, then the computational unit resembles the logistic regression model. The only difference between the ANN and regression models is the manner in which the values for the weights are established. ANNs employ a dynamic programming approach to iteratively adjust the weights until the error is minimized while the regression models compute the weights using a mathematical technique that minimizes the squared error (Brown et al., 2000, IBM Neural, 2010).

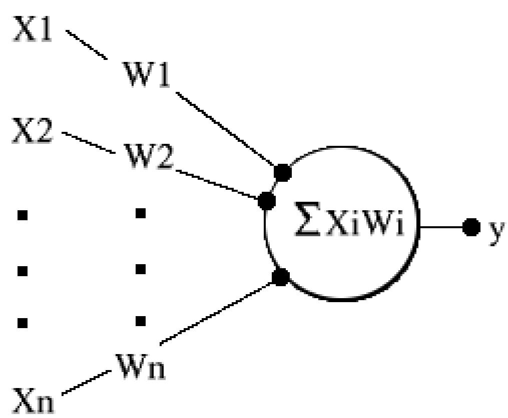


Figure 4: Structure of computational unit for node

A Multi Layer Perception (MLP) is typically composed of several layers of nodes. The first or the lowest layer is an input layer where external information is received. The last or the highest layer is an output layer where the problem solution is obtained. The input layer and output layer are separated by one or more intermediate layers called the hidden layers. The nodes in adjacent layers are usually fully connected by acyclic arcs from a lower layer to a higher layer. Figure 5 represents multi layer perception with two hidden layer. (Gallant, 1995)

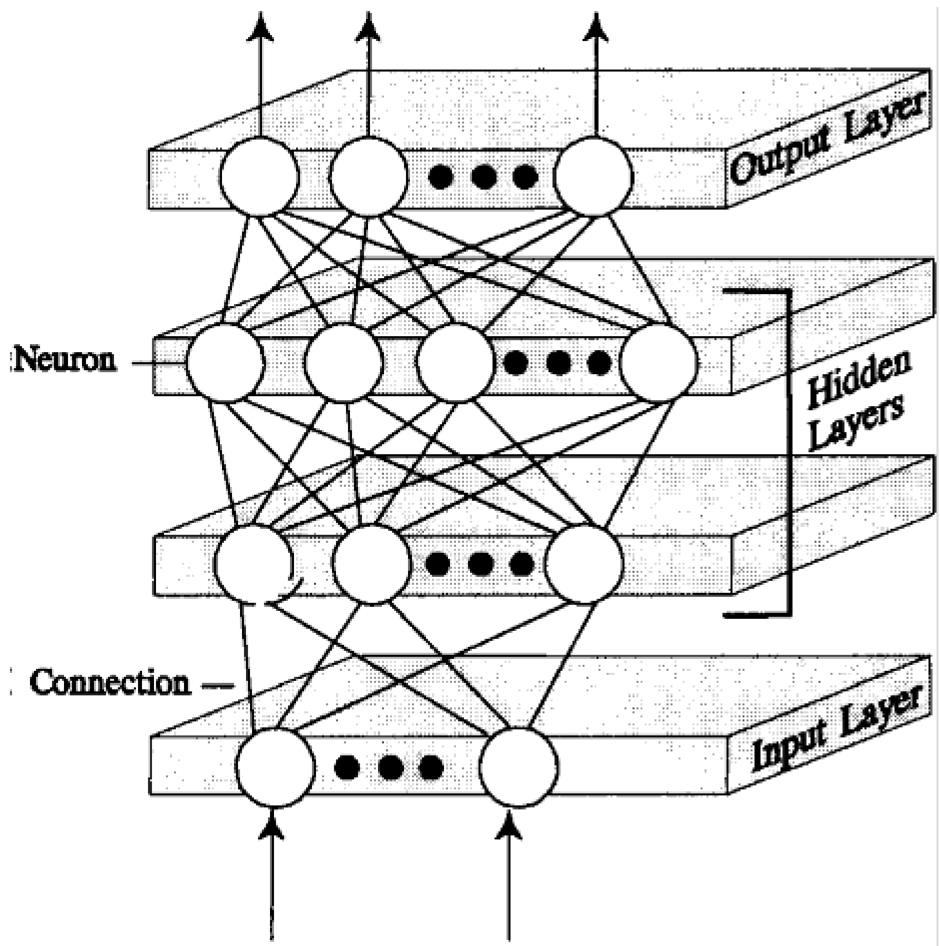


Figure 5: Neural network structure with two hidden layers
(Coakey, 2000)

The nodes are organized into a series of layers with an input layer, one or more hidden layers, and an output layer. Data flows through this network in one direction only, from the input layer to the output layer.

When a researcher decides to use neural networks in his or her study, the steps below needed to be decided (Brown et al., 2000):

1. The selection of the learning algorithm.
2. The choice of the error and transfer functions.
3. The specification of the architecture.
    a. The number of input nodes.
    b. The number of hidden layers and hidden nodes.
    c. The number of output nodes.
4. The appropriate preparation of data to match the architecture
5. The approach used to train network.

The process of learning is implemented by changing the weights until the desired response is attained at the output nodes. Two learning mechanisms can be used to derive the weights: unsupervised learning and supervised learning. In unsupervised learning the input patterns are classified according to their degree of similarity, with similar patterns activating the same output pattern. Supervised learning accepts input examples, computes the output values, compares the computed output values to the desired output values (termed target values), and then adjusts the network weights to reduce the difference (error). The most commonly used supervised learning algorithm is back propagation (Gallant, 1995). The sum-of-squared-error (SSE) function is the one most widely applied in the accounting and finance literature. The SSE function uniformly weights each training trial error in accordance with the square of the magnitude of the error vector (Target - Output). This error-measurement scheme ensures that large errors receive much greater attention than small errors. It is much more sensitive to errors made on commonly encountered inputs than it is to errors on rare inputs (Hecht-Nielsen, 1990). The transfer function is used to derive the output of a node given its weighted-adjusted input. If non-linear transfer functions are used, linear independence of the input patterns is not required. Thus, non-linear transfer functions allow ANN models to be applied to a wider range of problems (Hertz et al., 1991). In theory any differentiable function can be used. In literature three types of nonlinear functions are used in ANNs; sigmoid (logistic), half-sigmoid and hyperbolic tangent (Figure 6). Among those functions, it is not clear which activation function is better for system performance. While the majority of researchers use sigmoid activation functions for hidden nodes, there is no consensus on which activation function should be used for output nodes.

The sigmoid (logistic) function: $f(x) = (1+ \exp(-x))^{-1}$

The hyperbolic tangent (tanh) function: $f(x)=(\exp(x)-\exp(-x)) /(\exp(x)+\exp(-x))$

Half sigmoid function:

$$\frac{1 - e^{-k}}{1 + e^{-k}}$$

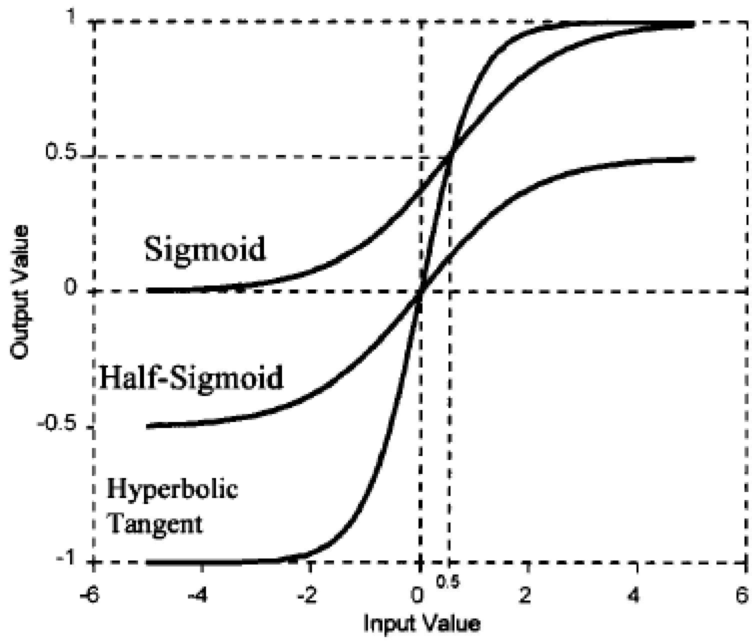


Figure 6: Nonlinear Transfer Functions
Coakey (2000)

Specification of neural network architecture begins with selecting number of input nodes. It is related with the selected topic. Input nodes are input parameters selected by the researcher which play important role for the value which will be forecasted. Then, number of hidden layers will be selected. Most authors use only one hidden layer for forecasting purposes. But there is no consensus about the number of hidden layers that should be used in forecasting. The most common way for determining the number of hidden layer and number of hidden nodes is making experiment or by trial and error. Single hidden layer is sufficient for ANNs to approximate any complex nonlinear function with any desired accuracy (Hornik et al., 1989). However, using two hidden layers may give better results for some specific problems, especially when one hidden layer network is overloaded with too many hidden nodes and with too many inputs

(Srinivasan et al., 1994). Two hidden layers are enough to solve most problems including forecasting (Lapedes & Farber, 1988). Number of hidden node is also is a debate in ANN design. Some practical suggestions for number of hidden nodes for one hidden layer are ‘‘2n+1’’ (Lippmann, 1987), ‘‘2n’’ (Wong, 1991), ‘‘n’ (Tang & Fishwick, 1993), ‘‘n/ 2’’ (Kang, 1991), where n is the number of input nodes. Today, developed ANN software like Neural Solutions can provide default values for hidden node by regarding the given data sample and number of hidden layers. Numbers of output nodes are the output parameters which will be forecasted by the system. After architecture is built, data will be prepared to use in the system. In this step data can be normalized in an interval such as between zero and one, data can be adjusted in the same scale like YTL to TL transformation is required for Turkish historical data since 6 digits are removed in the year 2005 or missing values in data replaced by a selected method. After transformation and data replacement, training and test samples are determined. In literature there is no ideal suggestion for division of training and testing samples but samples need to represent characteristics of researched question. Usually, data is divided as 90% training and 10 % testing sample in ANN tests. Sample size is also critical for helping neural system to improve learning, the larger the sample size, the more accurate results will be (Nam & Schaefer, 1995).

Artificial neural networks are used in forecasting in a wide range. The first application of ANN is a weather forecasting system by Hu (1964). After development of back propagation algorithm with ANN (Rumelhart et al., 1986), neural network approach has been being used in a variety of forecasting purposes. Some topics are bankruptcy, business failure, foreign exchange rate prediction, stock prices, electric load consumption, airborne pollen, commodity prices, temperature, helicopter component loads, airline passenger traffic, ozone level, personnel inventory, river flow, student grade point averages, total industry production, trajectory, transportation, water demand and wind pressure (Zhang et al., 1998).

Zhang et al. (1998) analyzed past studies which use artificial neural networks. The ANN designs of forecast models are recorded. Topics of research are not limited with finance and a variety of research fields are also demonstrated. Data type, training/testing size, number of input nodes, number of hidden layer and hidden nodes, output nodes, transfer function, training algorithm, data normalization and performance measurement parameters are demonstrated in Table 3. The calculation of performance measurements are:

The mean absolute deviation (MAD) = $\sum |e| / n$

The sum of squared error (SSE) = $\sum(e)^2$

The mean squared error (MSE)= $\sum(e)^2 / n$

The root mean squared error (RMSE) = $\sqrt{MSE}$

The mean absolute percentage error (MAPE) = $\frac{1}{N}\sum\frac{e}{y}(100)$

where e is the individual forecast error (forecasted – observed), y is the actual value, and N is the number of error terms.

Table 3: Summary of ANN Models (Zhang et al., 1998)

| Researchers | Data type | Training / test size | input nodes | Hidden layer / nodes | Output Nodes | Transfer fun. hidden:output | Training algorithm | Data normalization | Performance measure |
|---|---|---|---|---|---|---|---|---|---|
| Chakraborty et al. (1992) | Monthly price series | 90/10 | 8 | 1:8 | 1 | Sigmoid:sigmoid | BP* | Log transform. | MSE |
| Cottrell et al. (1995) | Yearly sunspots | 220/? | 4 | 1:2-5 | 1 | Sigmoid:linear | Second order | None | Residual varianc & BIC |
| De Groot and Wurtz (1991) | Yearly sunspots | 221/35,5 5 | 4 | 1:0-4 | 1 | Tanh:tanh | BP.BFGS LM** etc. | External linear to [0,1] | Residual variance |
| Foster et al. (1992) | Yearly and monthly data | *N-k*/k*** | 5,8 | 1:3,10 | 1 | N /A**** | N/A | N/A | MdAPE and GMARE |
| Ginzburg and Horn (1994) | Yearly sunspots | 220/35 | 12 | 1:3 | 1 | Sigmoid:linear | BP | Ext.l linear to [0,1] | RMSE |
| Gorret al. (1994) | Student GPA | 90%/10 % | 8 | 1:3 | 1 | Sigmoid:linear | BP | None | ME and MAD |
| Grudnitski and Osburn (1993) | Monthly S&P and gold | N/A | 24 | 2:(24)(8) | 1 | N/A | BP | N/A | % prediction accuracy |
| Kang (1991) | Simulated and real time series | 70/24 or 40/24 | 4,8,2 | 1,2:varied | 1 | Sigmoid:sigmoid | GRG2 | External linear [-1,1] or [0.1,0.9] | MSE, MAPE MAD, U-coeff. |
| Kohzadi et al. (1996) | Monthly cattle and wheat prices | 240/25 | 6 | 1:5 | 1 | N/A | BP | None | MSE, AME, MAPE |
| Kuan and Liu (1995) | Daily exchange rates | 1245/ varied | varied | 1:varied | 1 | Sigmoid:linear | Newton | N/A | RMSE |
| Lachtermacher and Fuller (1995) | Annual river flow and load | 100%/ synthetic | n/a | 1:n/a | 1 | Sigmoid:sigmoid | BP | External simple | RMSE and Rank Sum |
| Nam and Schaefer (1995) | Monthly airline traffic | 3,6,9 yrs/ 1 yr. | 12 | 1:12,15,17 | 1 | Sigmoid:sigmoid | BP | N/A | MAD |
| Nelson et al. (1994) | M-competition monthly | N-18/18 | varied | 1:varied | 1 | N/A | BP | None | MAPE |
| Schoneburg (1990) | Daily stock price | 42/56 | 10 | 2:(10)(10) | 1 | Sigmoid:sine, sigmoid | BP | External linear to [0.1,0.9] | % prediction accuracy |
| Sharda and Patil (1992) | M-competition time series | N-k/k*** | 12 for Monthl y | 1:12for monthly | 1,8 | Sigmoid:sigmoid | BP | Across channel linear [0.1,0.9] | MAPE |
| Srinivasan et al. (1994) | Daily load and relevant data | 84/21 | 14 | 2:(19)(6) | 1 | Sigmoid:linear | BP | Along channel to [0.1,0.9] | MAPE |
| Tang et al. (1991) | Monthly airline and car sales | N-24/24 | 1,6,12, 24 | 1: = input node [ | 1,6,12, 24 | Sigmoid:sigmoid | BP | N/A | SSE |
| Tang and Fishwick (1993) | M-competition | *N-k/k**** | 12:mo. 4:quar. | 1: = input node [ | 1,6,12 | Sigmoid:sigmoid | BP | External linear to [0.2,0.8] | MAPE |
| Vishwakarma (1994) | Monthly economic data | 300/24 | 6 | 2:(2)(2) | 1 | N/A | N/A | N/A | MAPE |
| Weigend et al. (1992) | Sunspots exchange rate (daily) | 221/59 501/215 | 12 61 | 1:8,3 1:5 | 1 1 | Sigmoid:linear Tanh:linear | BP | None along channel statistical | ARV ARV |

* Backpropagation
** Levenberg-Marquardt
*** *N* is the number of training sample size; *k* is 6, 8 and 18 for yearly, monthly and quarterly data respectively.
**** Not available

Zhang et al. (1998) also summarized studies which compares neural networks with traditional statistical methods. In most of the studies ANN showed greater performance.

Table 4: Comparison of ANN with traditional statistics (Zhang et al., 1998)

| Study | Data | Conclusion |
|---|---|---|
| Brace et al. (1991) | 8 electric load series (daily) | ANNs are not as good as traditional methods. |
| Caire et al. (1992) | One electric consumption data (daily) | ANNs are hardly better than ARIMA for 1- step-ahead forecast, but much more reliable for longer step-ahead forecasts. |
| Chakraborty et al. (1992) | One trivariate price time series (monthly) | ANNs outperform statistical model by at least one order of magnitude. |
| De Groot and Wurtz (1991) | Sunspots activity time series (yearly) | ANNs are not the best but comparable to the best linear or nonlinear statistical model. |
| Denton (1995) | Several computer generated data sets | Under ideal situations, ANNs are as good as regression; under less ideal situations, ANNs perform better. |
| Duliba (1991) | Transportation data (quarterly) | ANNs outperform linear regression model for random effects specification; but worse than the fixed effects specification. |
| Fishwick (1989) | Ballistic trajectory data | ANNs are worse than linear regression and surface response model. |
| Foster et al. (1992) | 384 economic and demographic time series (quarterly and yearly) | ANNs are significantly inferior to linear regression and simple average of exponential smoothing methods. |
| Gorr et al. (1994) | Student grade point averages | No significant improvement with ANNs in predicting students' GPAs over linear models. |
| Hann and Steurer (1996) | Weekly and monthly exchange rate | ANNs outperform the linear models for weekly data and both give almost the same results for monthly data. |

| | | |
|---|---|---|
| Hill et al. (1994) and Hill et al. (1996) | A systematic sample from 111 M-competition time series (monthly, quarterly and yearly) | ANNs are significantly better than statistical and human judgment methods for quarterly and monthly data; about the same for yearly data; ANNs seem to be better in forecasting monthly and quarterly data than in forecasting yearly data. |
| Kang (1991) | 50 M-competition time series | The best ANN model is always better than Box-Jenkins; ANNs perform better as forecasting horizon increases; ANNs need less data to perform as well as ARIMA. |
| Kohzadi et al. (1996) | Monthly live cattle and wheat prices | ANNs are considerably and consistently better and can find more turning points. |
| Lachtermacher and Fuller (1995) | 4 stationary river flow and 4 nonstationary electricity load time series (yearly) | For stationary time series, ANNs have a slightly better overall performance than traditional methods |
| Marquez et al. (1992) | Simulated data for 3 regression models | ANNs are almost much better than ARIMA. ANNs perform comparatively as well as regression models. |
| Nam and Schaefer (1995) | One airline passenger data (monthly) | ANNs are better than time series regression and exponential smoothing. |
| Refenes (1993) | One exchange rate time series (hourly) | ANNs are much better than exponential smoothing and ARIMA. |
| Sharda and Patil (1990) and Sharda and Patil (1992) | 75 and 111 M-competition time series (monthly, quarterly, and yearly) | ANNs are comparable to Box-Jenkins models. |
| Srinivasan et al. (1994) | One set of load data | ANNs are better than regression and ARIMA models. |
| Tang et al. (1991) | 3 business time series (monthly) | For long memory series, ANNs and ARIMA models are about the same; for short memory series, ANNs are better. |
| Tang and Fishwick (1993) | 14 M-competition time series and 2 additional business time series (monthly and quarterly) | Same as Tang et al. (1991) plus ANNs seem to be better as forecasting horizon increases. |
| Weigend et al. (1992) | Sunspots activity<br><br>Exchange rate (daily) | ANNs perform better than TAR and bilinear models.<br>ANNs are significantly better than random walk model. |

## Neural Networks Applications in Finance

Neural networks are used in academic studies for financial forecasting and they are also used in commercial software developed for banks and financial institutions. A software named FALCON was used by six of the ten largest credit card companies to screen transactions for potential fraud, and Inspector software was used by Chemical Bank to screen foreign currency transactions and several ANN software were used to assist investment decisions (Brown et al., 1995).

In recent researches, neural networks are used with other statistical methods and case based reasoning. Certain statistical values and technical indicators are used in neural networks as an input or output of ANNs is used in case based reasoning. This approach, called hybrid approach, is also suitable for fuzzy and genetic algorithms usage with ANNs. NEFCLASS (Neuro Fuzzy Classification, a NF approach for data analysis) used for training Early Warning System which has a three-layer feed-forward architecture and consists of input layer of 5 nodes and output layer of 3 nodes. It classified economic situation of South Korea as stable period, unstable period and crisis period. It performed two hundred and sixty three (90.07%) correct classifications and 29 (9.93%) incorrect classifications (Nauck, 2000). Enke & Amornwattana (2008) provided two hybrid system for return and volatility forecast for derivatives of S&P 500 index option, a financial instrument that is valued according to other underlying variables, prices (Table 5). Option is an interesting study because options allow investors to take large speculative position by using small capital. This study’s other difference is that it tries to forecast a price which depends on five different variables, including the current stock price, the strike price, the time to maturity, the risk-free rate, and the price volatility that are used to establish the option price. First hybrid system produces volatility forecast signal and uses that volatility signal to produce buy and sell signals according to forecasted volatility and case based reasoning. The other hybrid system produces return signal as primary signal and then use case based reasoning to buy and sell point for a given time. Generalized regression neural network and case based reasoning applied for historical data of S&P 500 index. Thawornwong (2003) suggested variables that are calculated from S&P 500 index's past data. As result, the system provides accurate forecasting for long term investment when two systems are used as a verification of another.

Table 5: Input and output variables

| Variable | Description |
|---|---|
| 01 | Trading month in year (e.g., 1 for January and 12 for December) |
| 02 | Trading date in months |
| 03 | Trading day in weeks (e.g., 1 for Monday and 5 for Friday) |
| 04-06 | Relative strength index at time t, t— 1, and t—2 |
| 07-09 | Money flow index at time t, t— 1, and t—2 |
| 10-12 | %K of the stochastic oscillator at time t, t-1, and t—2 |
| 13-15 | %D of the stochastic oscillator at time t, t—1, and t—2 |
| 16-18 | Moving average convergence/divergence at time t, t— 1, and t—2 |
| 19-21 | Signal line of moving average convergence/divergence at time t, t-1, and t-2 |
| 22-24 | Moving average minus closing price (C) at time t, t-1, and t-2 |
| 25-27 | Periodic compounding return at time t, t-1, and t—2 |
| 28-30 | 3-Month certificate of deposit: secondary market rate at time t, t-1, and t-2 |
| 31-33 | 3-Month treasury bill rate: secondary market rate at time t, t-1, and t-2 |
| 34-36 | 10-Year treasury constant maturity rate at time t, t— 1, and t-2 |
| 37-39 | 1-Year treasury constant maturity rate at time t, t—1, and t-2 |
| 40-42 | 3-Month treasury constant maturity rate at time t, t—1, and t-2 |
| 43^»5 | Bank prime loan rate at time t, t—1, and t—2 |
| 46-48 | Moody's seasoned Aaa corporate bond yield at time t, t-1, and t-2 |
| 49-51 | Moody's seasoned Baa corporate bond yield at time t, t-1, and t—2 |
| 52-54 | Effective federal funds rate at time t, t—1, and t—2 |
| Output | Direction of return at time t+1 compared to return at time t |

Majhi et al. (2009) developed a functional link artificial neural network (FLANN). The diagram of FLAAN can be seen in Figure 7.

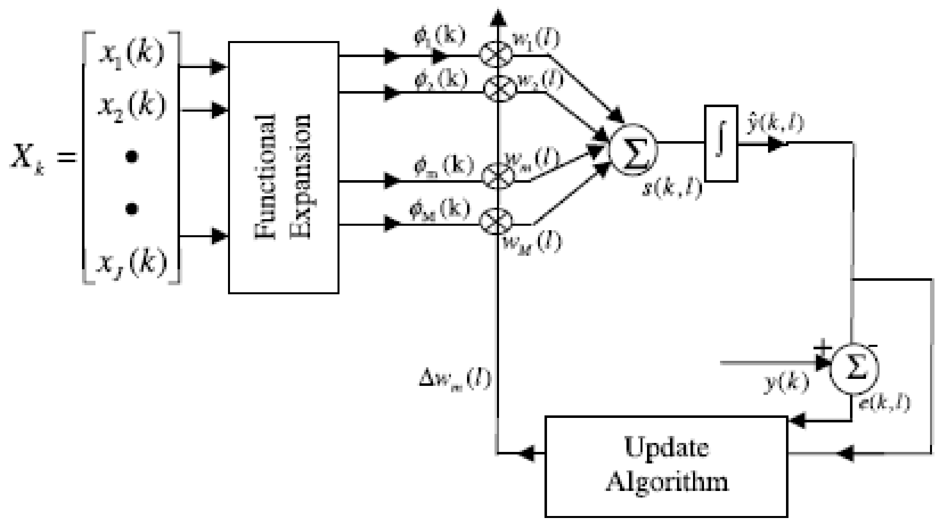


Figure 7: FLANN Model
(Majhi et al., 2009)

In the model each input turned to 5 variables. 4 variables are trigonometric functions applied to the input and the 5th one is the input itself. The trigonometric functions used are cos πx, sin πx, cos3πx, sin 3πx where x is an input. In updating network algorithm two functions; least mean square (LMS) and recursive last square (RLS) are used. So two models used in experiments are functional linked single layer artificial neural networks with least mean square (FLAAN – LMS) and functional linked single layer artificial neural networks with recursive last square (FLAAN – RLS).

The FLAAN uses ten technical indicators and macroeconomic variables as input and forecast Dow Jones Industrial Average (DJI) and Standard & Poor's 500 indices. The ten technical indicators used by Majhi are shown in Figure 8.

| Technical indicators | Formula |
|---|---|
| Simple moving average (SMA) | $\frac{1}{N}\sum_{i=1}^{N} x_i$, $N$ = No. of days, $x_i$ = today's price |
| Exponential moving average (EMA) | $(P \times A) + (\text{Previous EMA} \times (1 - A))$; $A = 2/(N + 1)$, $P$ – current price, $A$ – smoothing factor, $N$ – time period |
| Accumulation/ distribution oscillator (ADO) | $\frac{(C.P - L.P) - (H.P - C.P)}{(H.P - L.P) \times (\text{Period's Volume})}$ C.P – closing price, H.P – highest price, L.P – lowest price |
| Stochastic oscillator (STO) | $\%K = \frac{(\text{Today's Close} - \text{Lowest Low in } K \text{ period})}{(\text{Highest High in } K \text{ period} - \text{Lowest Low in } K \text{ period})} \times 100$ |
| | $\%D$ = SMA of $\%K$ for the period |
| On balance volume (OBV) | If Today's Close > Yesterday's Close OBV = Yesterday's OBV + Today's Volume If Today's Close < Yesterday's Close OBV = Yesterday's OBV – Today's volume |
| WILLIAM's %R | $\%R = \frac{(\text{Highest High in } n \text{ period} - \text{Today's Close})}{(\text{Highest High in } n \text{ period} - \text{Lowest Low in } n \text{ period})} \times 100$ |
| Relative strength index (RSI) | $\text{RSI} = 100 - \frac{100}{1 + (U/D)}$ $U$ = total gain/$n$, $D$ = total loss/$n$, $n$ = number of RSI period |
| Price rate of change (PROC) | $\frac{(\text{Today's Close} - \text{Close } X\text{-period ago})}{(\text{Close } X\text{-period ago})} \times 100$ |
| Closing price acceleration (CPACC) | $\frac{(\text{Close Price} - \text{Close Price } N\text{-period ago})}{(\text{Close Price } N\text{-period ago})} \times 100$ |
| High price acceleration (HPACC) | $\frac{(\text{High Price} - \text{High Price } N\text{-period ago})}{(\text{High Price } N\text{-period ago})} \times 100$ |

Figure 8: Technical Indicators
(Majhi et al., 2009)

Majhi et al. (2009) indicate that some inputs can forecast an index accurately for a certain time period but the same input combination might not forecast the same index in other time interval. The only way to find out which technical indicators should be selected is trial and error. Majhi provided the inputs and the forecasting results for indices in Table 6 and 7. The names and calculations of inputs can be found in Figure 8. Mean Absolute Percentage Error (MAPE) is used as measurement of success in forecasting results.

Table 6: Experiment results for one day advance period

| Stock index | Input variables to FLANN–LMS model | Testing period (days) | MAPE (%) |
|---|---|---|---|
| DJIA | EMA10, EMA30, ADO, CPACC, HPACC, STO, RSI9, PROC 12, PROC 27 | 390 | 0.64 |
| DJIA | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC12, PROC27, WILLIAMS | 658 | 0.74 |
| S&P 500 | EMA10, EMA30, ADO, CPACC, HPACC, STO, RSI9, PROC 12, PROC 27 | 390 | 0.61 |
| S&P 500 | EMA10, EMA30 ADO, CPACC, HPACC, STO, RSI9, PROC12, PROC27 | 658 | 0.65 |

Table 7: Experiment results for one month advance period

| Stock index | Input variables to FLANN–LMS model | Testing period (days) | MAPE (%) |
|---|---|---|---|
| DJIA | ADO, CPACC, HPACC, RSI9, RSI14, PROC12, PROC27, WILLIAMS, OBV,STO | 650 | 16.6 |
| DJIA | EMA10, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC12, PROC27, OBV, STO | 650 | 6.3 |
| DJIA | EMA10, EMA30 ADO, CPACC, HPACC, RSI9, PROC12, PROC27,OBV, STO, WILLIAMS | 650 | 5.9 |
| DJIA | EMA10, EMA30 ADO, CPACC, HPACC, RSI9, PROC12, PROC27,OBV, STO | 650 | 3.61 |
| DJIA | EMA10, EMA20, EMA30, PROC12, PROC27, RSI9, RSI14, STO | 650 | 3.03 |
| DJIA | EMA10, EMA20, EMA30, ADO, RSI9 | 650 | 2.92 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, RSI14 | 650 | 2.91 |
| DJIA | EMA10, EMA20, EMA30 | 650 | 2.88 |
| DJIA | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC12, PROC27, WILLIAMS, OBV, STO | 650 | 2.75 |
| DJIA | EMA 10, EMA 20, EMA 30, ADO, CPACC, HPACC, RSI 9, WILLIAMS | 60 | 1.39 |
| S&P 500 | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC12, PROC27, WILLIAMS, STO | 658 | 2.95 |
| S&P 500 | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC27, WILLIAMS | 658 | 2.66 |
| S&P 500 | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC27, WILLIAMS | 60 | 2.22 |
| S&P 500 | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, PROC12, PROC27, RSI9, RSI14 | 60 | 2.09 |

Majhi et al. (2009) also used technical indicators with fundamental factors and in trial and error experiments best forecasts are in Table 8, 9 and 10.

Table 8: FLAAN - RLS Model using fixed set of technical indicators and different combination of fundamental factors

| Stock index | Input variables to FLANN model (technical indicators) | Input variables to FLANN model (fundamental factors) | Testing period (days) | MAPE using RLS (%) | RLS initialization constant |
|---|---|---|---|---|---|
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Interest rate | 60 | 2.19 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Oil price | 60 | 2.20 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | GDP growth (quarterly) | 60 | 2.20 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | CPI rate | 60 | 2.19 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Corporate dividend rate | 60 | 2.19 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Interest rate, oil price | 60 | 2.20 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Dividend, interest rate, GDP growth rate | 60 | 2.19 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Dividend, interest rate, Oil price | 60 | 2.20 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, PROC12, PROC27 | Oil price, interest rate, GDP growth rate | 60 | 2.19 | 1000 |

Table 9: FLAAN - RLS Model using fixed fundamental factors and different combinations of technical indicators

| Stock index | Input variables to FLANN model (technical indicators) | Input variables to FLANN model (fundamental factors) | Testing period (days) | MAPE using RLS(%) | RLS initialization constant |
|---|---|---|---|---|---|
| DJIA | EMA10 | Dividend, interest rate, oil price, GDP rate | 60 | 2.36 | 1000 |
| DJIA | EMA10, EMA20, EMA30 | Dividend, interest rate, oil price, GDP rate | 60 | 2.23 | 1000 |
| DJIA | EMA10, EMA20, EMA30, ADO | Dividend, interest rate, oil price, GDP rate | 60 | 2.42 | 1000 |
| DJIA | EMA10, EMA20, EMA30, HPACC | Dividend, interest rate, oil price, GDP rate | 60 | 2.21 | 1000 |
| DJIA | EMA10, EMA20, EMA30, CPACC | Dividend, interest rate, oil price, GDP rate | 60 | 2.24 | 1000 |
| DJIA | EMA10, EMA20, EMA30, RSI9 | Dividend, interest rate, oil price, GDP rate | 60 | 2.33 | 1000 |
| DJIA | EMA10, EMA20, EMA30, PROC12 | Dividend, interest rate, oil price, GDP rate | 60 | 2.38 | 1000 |
| DJIA | EMA10, EMA20, EMA30, STO | Dividend, interest rate, oil price, GDP rate | 60 | 2.52 | 1000 |
| DJIA | EMA10, EMA20, EMA30, WILLIAMS | Dividend, interest rate, oil price, GDP rate | 60 | 2.51 | 1000 |
| DJIA | EMA10, EMA20, EMA30, OBV | Dividend, interest rate, oil price, GDP rate | 60 | 2.07 | 1000 |

Table 10: Comparison of FLANN - RLS and FLANN – LMS

| Stock index | Input variables to FLANN | Days in advance Prediction | Testing period(days) | MAPE (LMS) (%) | MAPE (RLS) (%) |
|---|---|---|---|---|---|
| DJIA | EMA20, EMA30, ADO, CPACC, RSI9, RSI14, OBV, PROC 27, WILLIAMS | 60 days | 60 | 2.25 | 2.45 |
| DJIA | EMA10, EMA20, EMA30, ADO, CPACC, HPACC, RSI9, WILLIAMS | 30 days | 60 | 2.33 | 2.54 |
| DJIA | EMA10, EMA30, ADO, CPACC, HPACC, STO, RSI9, PROC 12, PROC 27 | 1 day | 390 | 0.64 | 0.5S |
| DJIA | EMA10, EMA20, EMA30 ADO, CPACC, HPACC, RSI9, RSI14, PROC12, PROC27, WILLIAMS | 1 day | 65S | 0.74 | 0.61 |

Technical and fundamental variables enable neural networks to make good forecast for stock indices when the variables are used in neural networks. The uses of all technical or all fundamental variables are unnecessary, because they do not increase prediction performance of the system. In addition, they increase computational afford and time. Certain technical indicators provide better performance result than other indicators for certain time period but only way to find best technical and fundamental factors is trial and error (Majhi et al., 2009).

CHAPTER III

# METHODOLOGY

## Model Development

Among alternative forecasting methods, artificial neural network approach is chosen because ANN can tolerate noise data of stock exchange, ANN can detect hidden relationships among input parameters and ANN is very good at finding patterns of data. Input parameters are highly related with each other because the stocks of the same sector will be used as input. The macroeconomic and sector specific factors are expected to affect the stocks in the same sector as the similar way. Also ANN can learn behavior of a sector by mastering past data.

Basically, the model takes inputs and produces a forecast for next séance's closing value (Figure 9). Inputs are the sub index's minimum and maximum values in previous séance as well as different combination of each stock's values in previous séance. Forecasted sector's closing value will be for séance 1 and 2 by taking values of séance 1 and 2, for only séance 2 by taking only séance 2's value and for only séance 1 by taking séance 1's values into account.

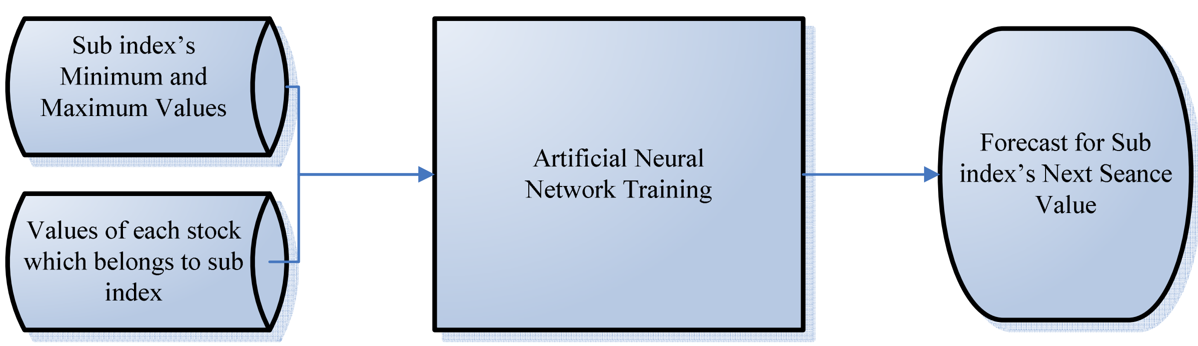


Figure 9: Simple Schema of System

In neural network design, model suggestion of Egeli et al. (2003) will be taken which has one hidden layer and uses Generalized Feed Forward (GFF) network structure. Because this network structure performed better than multi layer perception networks which has 1, 2, 3 or 4 hidden layers and GFF networks with 2,3,4 hidden layers in stock exchange prediction tests. Also one hidden layer structure has less computation time and effort compared to more hidden layers.

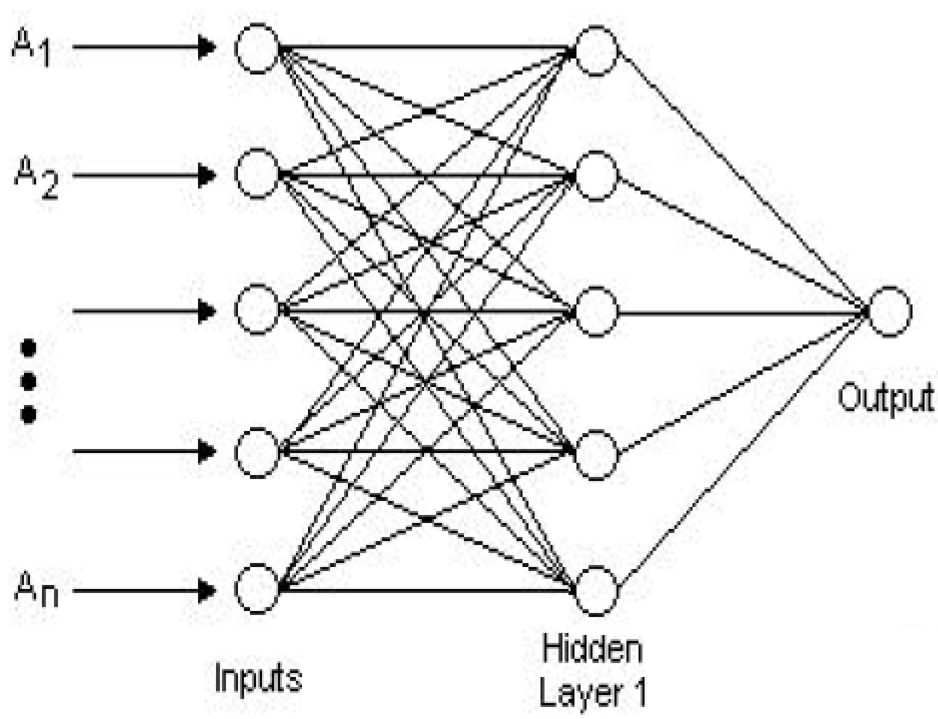


Figure 10: Hidden Layer Networks with n inputs and 1 output

Inputs are previous séance's maximum and minimum value of the sub index, and values of stocks which belongs to that sub index. Output is the next séance's closing value. %90 of all data set is used as training sample and remaining %10 constituted the testing data set.

## Data Preparation and Transformation

Firstly data is requested from IMKB information technologies center. Historical data is provided for stocks and indices. For each stock, date, séance, closing price, weighted average price (WAP), minimum price, maximum price, trading volume, traded value and number of contracts is provided. Trading volume indicates total number of buying and selling transaction in each séance. Traded value is the sum of total money in trading executions. For each index date, séance number, closing value, minimum value and maximum value are given. Data contains information from 1988 until 2010.

The beginning dates of indices are different. Some indices began to be calculated in 1997, some are in 2000. The oldest indices are XUMAL – National Finance Index and XUSIN – National Industry Index which is started in 1991. In 2005 Turkish Lira is changed to New Turkish Lira and 6 digits are removed from banknotes. In stock calculations pricing values are divided by 1000 to scale measurement.

Index and stock values are joined by date and séance. For each séance, index's closing value, minimum value, and maximum value are retrieved. For each stock, which belongs to that index, values of closing price, weighted average price, minimum price, maximum price, trading volume, traded value and number of contracts are queried and joined with index values in the same row, so that data became ready in spreadsheet for neural software.

Average price of a stock might not indicate that the stock price is increased, has not changed or decreased when compared to previous day. So, sign of the stock is added to input variables by subtracting closing price of that stock from previous day's closing price and taking the sign of the result. That is; if stock price is increased the sign becomes +1, if price has not changed sign becomes 0 and if price is decreased sign becomes -1.

There are 30 indices in Istanbul Stock Exchange. Some of these indices have small number of stocks. For example, sport index has 4 stocks, communication index has 2 stocks and transportation index has 4 stocks. Also there are indices where number of stocks is large. For example, national financial index has 70 stocks, chemistry index has 20 stocks and banking index has 18 stocks. In this study indices with different sizes are chosen randomly. It is more important to make forecast for big indices because their market share is huge. So, three big indices are chosen. One of small and one of mediate indexes are added to forecasts. No new stocks are added to electricity index and its computation afford is very low. So electricity index is also chosen because there will be only one test for electricity. XTRZM and XELKT with 5 stocks are selected as small indices, XBLSM with 12 stocks as a medium index and XGIDA with 20 stocks, XKMY with 20 stocks, XBANK with 20 stocks as large indices. Sectors' data are trained and tested for different time intervals. In historical tests all tests are made for year 2009 which is an increasing or steady trend in all sectors. But in sector based tests all increase, steady and decreasing trends are tested.

## Artificial Neural Network Test

### Input parameters

NeuroSolutions software is used with the default values for number of nodes in hidden layer and weight update default value is batch. The parameters are specified as; network type being General Feed Forward (GFF), mean standard error (MSE) threshold 0.0005, number of hidden layers being 1, transfer function being linear sigmoid and maximum epoch being 10,000 (Egeli et al., 2003).

### Input models

Different combinations of inputs are grouped as an input model. Those models are used in tests for finding the best input combination for making forecasts.

Table 11: Input Models

| Model Name | Input Values |
|---|---|
| Model1 | WAP, change, trading volume, number of contract of stocks, index's max and min values. |
| Model2 | Change, trading volume, number of contract of stocks, index's max and min values. |
| Model3 | WAP, trading volume, number of contract of stocks, index's max and min values. |
| Model4 | Trading volume, number of contract of stocks, index's max and min values. |

Output parameters

Performance indicators of NeuroSolutions software are Mean Squared Error (MSE), Normalized Mean Squared Error (NMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), minimum absolute error, maximum absolute error, and linear correlation coefficint (r).

MSE: Mean Squared Error

The mean squared error of an estimator $\hat{\theta}$ of a parameter $\theta$ in a statistical model is defined as (Planetmath 2010):

$$\operatorname{MSE}(\hat{\theta}) = \operatorname{E}\left[(\hat{\theta} - \theta)^2\right].$$

In our model, MSE is taking average of square of prediction of sub-index minus observed value of sub-index.

NMSE: Normalized Mean Squared Error (MSE/variance of desired output)

The NMSE is an estimator of the overall deviations between predicted and measured values. It is defined as:

$$NMSE = \frac{1}{N}\sum_i \frac{(P_i - M_i)^2}{\overline{P}\,\overline{M}}$$

$$\overline{P} = \frac{1}{N}\sum_i P_i$$

$$\overline{M} = \frac{1}{N}\sum_i M_i$$

In NMSE, the deviations (absolute values) are summed instead of the differences. For this reason, the NMSE generally shows the most striking differences among models. If a model has a very low NMSE, then it is well performing both in space and time. On the other hand, high NMSE values do not necessarily mean that a model is completely wrong. That case could be due to time and/or space shifting. Moreover, it must be pointed out that differences on peaks have a higher weight on NMSE than differences on other values. The confidence interval for the NMSE cannot be computed from a known distribution. The bootstrap technique has to be used (Europa, 2010).

<u>MAE:</u> Mean Absolute Error

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|\,.$$

The mean absolute error is the average of the absolute errors $e_i = f_i - y_i$, where $f_i$ is the prediction and $y_i$ is the real value. Note that alternative formulations may include relative frequencies as weight factors. (Wiki MAE, 2010)

<u>MAPE:</u> Mean Absolute Percentage Error

$$\text{MAPE} = \frac{1}{N}\sum\frac{e}{y}\ (100)$$

where e is the individual forecast error (forecasted – observed), y is the actual value, and N is the number of error terms.

<u>Min Abs Error:</u> Minimum absolute error

The minimum of absolute value of forecasted value subtracted from actual value. It is the closest or the best forecast in the system.

<u>Max Abs Error:</u> Maximum absolute error

The maximum of absolute value of forecasted value subtracted from actual value. It is the worst forecast in the system.

r: Linear Correlation Coefficient

r is computed as:

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \left( \frac{X_i - \bar{X}}{s_X} \right) \left( \frac{Y_i - \bar{Y}}{s_Y} \right)$$

where $\bar{\mathbf{X}}$ and $\bar{\mathbf{Y}}$ are the sample means of X and Y, $S_x$ and $S_y$ are the sample standard deviations of X and Y. The correlation coefficient ranges from −1 to 1. A value of 1 implies that a linear equation describes the relationship between X and Y perfectly, with all data points lying on a line for which Y increases as X increases. A value of −1 implies that all data points lie on a line for which Y decreases as X increases. A value of 0 implies that there is no linear correlation between the variables (Wiki r, 2010).

## Tests

After data preparation, tests in neural network software began. Previous day's values are used to forecast next day's index value. After preliminary tests, it is derived that input values which are derivative of another input variable need not to be included such as total volume, multiplication of average price and trading volume, and volume. Closing values of stocks constitute previous day's index closing price directly and that situation confuses back propagation of neural network algorithm so they are discarded too.

Firstly tourism index is tested. Traded value and number of contracts details are included in all tests. Tests used different combinations of input parameters of sign of stocks and average price of stocks. Also different tests are performed in séance basis too that is; tests performed for considering just séance 1 or just séance 2. When a new stock is added to the index, it affects the index according to market value of that stock. Here the addition of new stock causes a trade off between losing historical data from other stock and adding new stock, because in the software it is not possible to use null values for newly added stocks in past days. Summary of test results are provided in tables 11 and 12. Lower mean absolute percentage error means better forecast. Also r value which approaches to 1 indicates better prediction quality.

## Historical Tests

In historical tests, date is taken from the beginning of data provided to the end date. If a new stock is added to the index then it is disregarded to protect historical pattern. The new stock's data is considered in another step beginning from the addition date of the new stock until the end. In all tests % 90 of all date are taken as training set, remaining %10 are taken as testing set. Results indicate the forecast results of last %10 portion of time period. Input model is illustrated in Table 11.

Table 12: Tests with Historical Data

| | Index | Inputs | Time Period | r | MAPE |
|---|---|---|---|---|---|
| 1 | XTRZM séance 1 and 2 | Model1 | 1997-01-02 to 2009-12-30 | 0.94 | % 7.03 |
| 2 | XTRZM séance 1 and 2 | Model1 | 2000-08-10 to 2009-12-30 | 0.96 | % 5.95 |
| 3 | XTRZM for séance 1 and 2 | Model1 | 2000-08-31 to 2009-12-30 | 0.94 | %8.16 |
| 4 | XTRZM for séance 1 and 2 | Model1 | 2009-01-02 to 2009-12-30 | 0.52 | %1.94 |
| 5 | XTRZM for séance 1 and 2 | Model2 | 1997-01-02 to 2009-12-30 | 0.97 | %6.91 |
| 6 | XTRZM for séance 1 and 2 | Model2 | 2000-08-10 to 2009-12-30 | 0.97 | %5.54 |
| 7 | XTRZM for séance 1 and 2 | Model2 | 2000-08-31 to 2009-12-30 | 0.96 | %6.73 |
| 8 | XTRZM for séance 1 and 2 | Model2 | 2009-01-02 to 2009-12-30 | 0.45 | %2.27 |
| 9 | XTRZM for séance 1 and 2 | Model4 | 1997-01-02 to 2009-12-30 | 0.94 | %6.91 |
| 10 | XTRZM for séance 1 and 2 | Model4 | 2000-08-10 to 2009-12-30 | 0.96 | %5.85 |
| 11 | XTRZM for séance 1 and 2 | Model4 | 2000-08-31 to 2009-12-30 | 0.96 | %6.18 |
| 12 | XTRZM for séance 1 and 2 | Model4 | 2009-01-02 to 2009-12-30 | 0.43 | %2.30 |
| 13 | XTRZM for séance 2 | Model1 | 1997-01-02 to 2009-12-30 | 0.93 | %14.86 |
| 14 | XTRZM for séance 2 | Model1 | 2000-08-31 to 2009-12-30 | 0.97 | %4.85 |

| | | | | | |
|---|---|---|---|---|---|
| 15 | XTRZM for séance 2 | Model1 | 2009-01-02 to 2009-12-30 | 0.47 | %1.90 |
| 16 | XTRZM for séance 2 | Model2 | 1997-01-02 to 2009-12-30 | 0.94 | %9.68 |
| 17 | XTRZM for séance 2 | Model2 | 2000-08-31 to 2009-12-30 | 0.96 | %6.91 |
| 18 | XTRZM for séance 2 | Model2 | 2009-01-02 to 2009-12-30 | 0.03 | %2.34 |
| 19 | XTRZM for séance 2 | Model4 | 1997-01-02 to 2009-12-30 | 0.99 | %5.62 |
| 20 | XTRZM for séance 2 | Model4 | 2000-08-31 to 2009-12-30 | 0.97 | %4.46 |
| 21 | XTRZM for séance 2 | Model4 | 2009-01-02 to 2009-12-30 | 0.34 | %2.23 |
| 22 | XTRZM for séance 1 | Model3 | 1997-01-02 to 2009-12-30 | 0.84 | %6.37 |
| 23 | XTRZM for séance 1 | Model3 | 2000-08-31 to 2009-12-30 | 0.96 | %4.73 |
| 24 | XTRZM for séance 1 | Model3 | 2009-01-02 to 2009-12-30 | 0.58 | %1.98 |
| 25 | XTRZM for séance 1 | Model4 | 1997-01-02 to 2009-12-30 | 0.82 | %2.89 |
| 26 | XTRZM for séance 1 | Model4 | 2000-08-31 to 2009-12-30 | 0.97 | %5.59 |
| 27 | XKMY for séance 1 and 2 | Model1 | 1997-01-02 to 2009-12-31 | 0.58 | %13.46 |
| 28 | XKMY for séance 1 and 2 | Model1 | 1999-11-03 to 2009-12-31 | 0.86 | %9.18 |
| 29 | XKMY for séance 1 and 2 | Model1 | 2001-01-02 to 2009-12-31 | 0.36 | %16.26 |
| 30 | XGIDA for séance 1 and 2 | Model1 | 1997-01-02 to 2009-12-31 | 0.97 | %4.59 |
| 31 | XGIDA for séance 1 and 2 | Model1 | 2000-08-11 to 2009-12-31 | 0.92 | %7.80 |
| 32 | XELKT for séance 1 and 2 | Model1 | 2000-07-07 to 2009-12-31 | 0.94 | %6.40 |
| 33 | XBLSM for séance 1 and 2 | Model1 | 2000-11-02 to 2009-12-31 | 0.49 | %27.54 |
| 34 | XBLSM for séance 1 and 2 | Model1 | 2004-08-19 to 2009-12-31 | 0.69 | %9.30 |
| 35 | XBANK for séance 1 and 2 | Model1 | 1997-01-02 to 2009-12-31 | 0.96 | %7.36 |
| 36 | XBANK for séance 1 and 2 | Model1 | 1997-04-10 to 2009-12-31 | 0.96 | %6.09 |
| 37 | XBANK for séance 1 and 2 | Model1 | 2000-08-28 to 2009-12-31 | 0.97 | %6.76 |
| 38 | XBANK for séance 1 and 2 | Model1 | 2004-10-01 to 2009-12-31 | 0.96 | %3.69 |

| | | | | | |
|---|---|---|---|---|---|
| 39 | XBANK for séance 1 and 2 | Model1 | 2006-05-12 to 2009-12-31 | 0.73 | %3.63 |
| 40 | XBANK for séance 1 and 2 | Model1 | 2007-06-29 to 2009-12-31 | 0.73 | %4.53 |

Graphical representation of results can be found in Appendix A. Other measurement of success parameters; MAE, MSE, NMSE, Minimum Abs Error and Maximum Abs Error are also listed in Appendix A.

## Stock Based Tests

In stock based tests, all of the stocks constituting that index for a certain period of time are taken into account. Test intervals are beginning of index recording to a new stock issued to the market. When another stock is added to the index, again a new time interval and a new test period occurs. In all tests % 90 of all dates are taken as training set, remaining %10 are taken as testing set. Results indicate the forecast results of last %10 portion of time interval.

Table 13: Stock Based Tests

| | Index | Inputs | Time Period | r | MAPE |
|---|---|---|---|---|---|
| 41 | XTRZM séance 1 and 2 | Model1 | 1997-01-02 to 2000-08-09 | 0.74 | %4.80 |
| 42 | XTRZM séance 1 and 2 | Model1 | 2000-08-31 to 2008-12-30 | 0.97 | %5.06 |
| 43 | XTRZM for séance 1 and 2 | Model1 | 2000-01-02 to 2009-12-30 | 0.55 | %5.13 |
| 44 | XTRZM for séance 1 and 2 | Model2 | 1997-01-02 to 2000-08-09 | 0.68 | %5.01 |
| 45 | XTRZM for séance 1 and 2 | Model2 | 2000-08-31 to 2008-12-31 | 0.96 | %6.44 |
| 46 | XTRZM for séance 1 and 2 | Model2 | 2009-01-02 to 2009-12-30 | 0.02 | %2.09 |
| 47 | XTRZM for séance 1 and 2 | Model4 | 1997-01-02 to 2000-08-09 | 0.75 | %3.94 |
| 48 | XTRZM for séance 1 and 2 | Model4 | 2000-08-31 to 2008-12-31 | 0.97 | %6.78 |
| 49 | XTRZM for séance 1 and 2 | Model4 | 2009-01-02 to 2009-12-30 | 0.47 | %2.16 |
| 50 | XKMY for séance 1 and 2 | Model1 | 1997-01-02 to 1999-11-03 | 0.34 | %13.28 |
| 51 | XKMY for séance 1 and 2 | Model1 | 1999-11-03 to 2000-12-22 | 0.89 | %7.00 |
| 52 | XKMY for séance 1 and 2 | Model1 | 2001-01-02 to 2001-12-28 | 0.82 | %3.20 |
| 53 | XKMY for séance 1 and 2 | Model1 | 2003-01-02 to 2009-12-31 | 0.89 | %9.30 |
| 54 | XGIDA for séance 1 and 2 | Model1 | 1997-01-02 to 1997-08-18 | 0.78 | %2.25 |

| | | | | | |
|---|---|---|---|---|---|
| 55 | XGIDA for séance 1 and 2 | Model1 | 2000-08-11 to 2004-02-20 | 0.92 | %5.02 |
| 56 | XGIDA for séance 1 and 2 | Model1 | 2004-02-23 to 2005-05-11 | 0.60 | %11.15 |
| 57 | XGIDA for séance 1 and 2 | Model1 | 2006-05-12 to 2009-12-31 | 0.86 | %2.39 |
| 58 | XBLSM for séance 1 and 2 | Model1 | 2000-11-02 to 2004-06-18 | 0.89 | %9.00 |
| 59 | XBLSM for séance 1 and 2 | Model1 | 2004-08-19 to 2005-09-12 | 0.82 | %2.51 |
| 60 | XBLSM for séance 1 and 2 | Model1 | 2006-10-20 to 2009-12-31 | 0.85 | %3.50 |
| 61 | XBANK for séance 1 and 2 | Model1 | 1997-01-02 to 1997-04-09 | 0.68 | %1.77 |
| 62 | XBANK for séance 1 and 2 | Model1 | 2000-02-28 to 2004-09-30 | 0.97 | %1.84 |
| 63 | XBANK for séance 1 and 2 | Model1 | 2004-10-01 to 2005-11-17 | 0.61 | %14.53 |
| 64 | XBANK for séance 1 and 2 | Model1 | 2006-05-12 to 2007-05-09 | 0.81 | %2.41 |
| 65 | XBANK for séance 1 and 2 | Model1 | 2007-06-29 to 2009-12-31 | 0.83 | %2.39 |

Each experiment's details are listed in Appendix A. For each test graphical representation of %10 percent testing results, and other measurement of success parameters are also provided in Appendix A.

# CHAPTER IV

## FINDINGS AND DISCUSSION

This study's aim is to investigate if it is a good way to forecast sector indices instead of forecasting overall index or selecting individual stocks. In literature, there is not a research aimed to make forecast for sector indices. Stocks which belong to a sector index are analyzed together in the study. Since artificial neural networks (ANNs) find out the hidden relationships among inputs and the relationship between inputs and output, it is expected from ANN to make good forecast. Moreover, the behavior of sector index might be easier to catch for neural networks to discover patterns of sector index. ANN can learn from technical indicators of a sector index by mastering past data. Also the fundamental economic factors affect a sector's stock in similar way. An increase in a stock might be an early indicator for other stocks in the same index. The ANN can discover it but since ANN is a black box model, the researcher cannot explain the economics judgment. A national stock index consists of many different sectors which behave in its own way. Fundamental and technical factors affect the sectors differently and overall index forecasting might be more confusing for ANN to learn.

Firstly it is questioned to find the best variables among all variables on hand. The previous séance's maximum and minimum values of sector index are taken as input to forecast next séance. The previous séance's closing value is already counted as output in previous séance. ANN takes in to account this closing price too. Weighted average price, trading volume, number of contract and change (sign) of stocks are also regarded in forecasting.

First of all, it is derived from tests that enough observation is required for an ANN to make good forecast. ANN cannot make good prediction for limited observations. In tests 4, 8, 12, 15, 18, 21 and 24 number of observations is lower than 100 and r values are very low ($r < 0.5$) which indicates low quality in prediction. So in all tests neural network need approximately 100 tests and 900 training observations.

In first tests with XTRZM – Tourism index of IMKB, different combination of WAP and change variables of stocks are tested in historical tests. When we compare test 1 with test 5 (historical tests with two stocks), all the other things are constant except test 5 does not contain WAP. In test 5 removing WAP increased prediction performance slightly compared to test 1. MAE decreased from 320 to 309 and r value increased from 0.96 to 0.97. The same situation observed for comparison of test 2 with 6, test 3 with 7 (Historical tests for tourism indices all things constant except WAP). However for tests 4 and 8 (Historical tests for tourism indices all things constant except WAP) the improvement in forecasting is not observed. The situation supported in tests made for forecasting séance 2 only; removing WAP increased performance in tests 16 (forecast for tourism just séance 2 with WAP) as compared to test 13 (historical forecast for tourism just séance 2 without WAP) but decreased it in test 17 (historical forecast for tourism just séance 2 with WAP) compared to 14 (historical forecast for tourism just séance 2 without WAP). On the other hand, removing WAP in some stock based tests decreased performance. When we compare test 45 (stock based forecast for XTRZM séance 1 and 2 without WAP) with 42 (stock based forecast for XTRZM séance 1 and 2 with WAP), removing WAP increased MAE from 235 to 280 and decreased r from 0.97 to 0.96.

When we analyze the effect of change (sign) variable on performance, it is derived that removing change variable decrease performance slightly in all tests. But again it does not play a critical role, the effect is limited. Test 9 (historical test for tourism séance 1 and 2 without change, without WAP) is slightly worse than test 5 (historical test for tourism séance 1 and 2 without WAP); test 10 (historical test for tourism séance 1 and 2 without change, without WAP) is again a little worse than test 6 (historical test for tourism séance 1 and 2 without WAP) and other tests too.

So it is derived that making prediction with change and WAP is a little different than making prediction without removing one or both variables. Removing change decreased performance slightly in all tests. Disregarding WAP decreased performance in some tests, but in majority it makes a little more improvement. The only way to find out which variables provide better performance is trial and error. But tests with considering these two variables of all stocks do not have significant difference. So other sector indices will be predicted by using the two variables.

Another research topic is that making forecast for only séance 2 by considering past data of séance 2 and making prediction for séance 1 by considering past values of séance 1 provide better performance. A historical test for séance 2 of XTRZM performed worse than the same situation for séance 1 and 2 of test 1. But test 14 (historical test for tourism just séance 2) is better than test 2 (historical test for tourism séance 1 and 2) again in the same situation. The best r value is obtained from test 19. It is for séance 2 without WAP and without change. But prediction for séance 2 does not always provide better performance. The same situation is observed for forecasts for just séance 1 by regarding only past data of séance 1. Test 26 (historical test for tourism séance 1) is slightly better than test 11 (historical test for tourism séance 1 and 2). But again the only way is trial and error to find the best combination.

Another important topic of this research is selecting forecasting approach. The historical approach or stock based approach should be decided. The historical approach ignores the addition of new stocks in to the index and preserves all the past data. So that neural network gathers more information and neural network's learning ability of patterns increases. XTRZM, for example, begins with 2 stocks in 1997 and until 2000; it remains with the same 2 stocks. In the year 2000 new stocks are added to index. If a researcher wants to use the new stocks, the other 2 stocks' 3 year data cannot be used. So a new approach is considered and stock based is tested. In stock based approach only stocks constituting the index is considered in forecasting that index. That is, from 1997 – 2000 2 stocks are counted in forecasting. After issuing new stocks, the data before 2000 is not used. Only data of 2000 and newer are regarded in stock based approach from test 41 to 90. Historical tests are from 1 to 40. When we compare successfulness of those tests, generally stock based tests performed better. In historical tests with XBLSM and XKMY are failed (tests 27, 28, 29, 33, 34). But stock based tests with those indices become successful (Tests 51, 53, 58, 59, 60). On the other hand, not all tests with stock based approach are successful. Test 50 which is a stock based test, completely failed for XKMY. So for certain time periods, forecasting with stock based approach are applicable for certain indices but not all time intervals. If new stocks are added an index frequently, it will become difficult for neural network to collect enough observation. Tests 61, 63, 64 (stock based tests) cannot make good prediction because of limited observation. But test 38, which is a historical test, is a better forecast then tests 61, 63 and 64 because historical approach provide more observation for banking index in this period. So it can be generalized that stock based approach is better than historical approach if there is enough sample. But in some cases it is required to use historical approach and disregard new added stocks to collect enough observation. Also some historical tests with small data are better than historical tests with more data like test 2 (historical test for tourism) is better than test 1 (historical test for tourism) but worse than test 3 (historical test for tourism). Test 2 has 3 stocks, test 1 has 2 and test 3 has 4 stocks. All of them forecasted index with 5 stocks but the best one is test 2. So if a situation requires historical tests, it should be tested with all possible historical tests.

After it is found out that stock based approach performed better in most of the cases, another interesting situation has emerged. For some tests, the artificial neural network algorithm successfully forecast some part of data but not other parts are forecasted well, such as test 42, 55, 58 and 62. Test 55, for example, performed good until 100$^{th}$ forecast but it could not make good forecast after 100$^{th}$ forecast. In literature, Srinivasan et al. (1994) demonstrated that one hidden layer might be overloaded with too many input parameters and using two hidden layer might provide better forecast. So, new tests are performed with two hidden layer architecture. It is tested if architecture with two hidden layers is capable of prediction without that confusion. But two hidden layer networks performed worse in all cases. So one hidden layer structure design of Egeli et al. (2003) is verified.

Table 14: One hidden layer vs. two hidden layers

| Test No | One Hidden Layer | | Two Hidden Layer | |
|---|---|---|---|---|
| | r | MAE | r | MAE |
| 42 | 0.97 | 235 | 0.93 | 436 |
| 55 | 0.92 | 885 | 0.38 | 698 |
| 58 | 0.89 | 591 | 0.51 | 769 |
| 62 | 0.97 | 545 | 0.92 | 788 |

Different types of stock exchange prediction studies performed by researchers for decades. This study opens a way for forecasting stock exchange which is not used. This study can be expanded by including hourly data of stocks and indices and this data addition enables neural networks to learn hourly behavior in a day. So that instead of closing value of séance, maximum value can be forecasted.

This study can also be elaborated by addition of technical indicators like William indicator, exponential moving average and stochastic oscillator indicator and other technical indicators. These indicators can be calculated for stocks or for sector index.

Also fundamental indicators like oil price, GDP, interest rate and exchange rates can be included in input set. Some indicators can be more meaningful for a sector and the same indicator might not carry too much importance for other sectors. Sector based approach can enable making such distinction.

Finally, correlation analysis among sector indices can be used in forecasting or case based approach. Correlation between national index and sector indices can also be meaningful for prediction.

CHAPTER V

# SUMMARY AND CONCLUSION

Stock exchange prediction is a challenging topic and many academicians and software development companies are interested in forecasting stock exchanges. This study claim that forecasting sector indices can be regarded as one of the alternative ways in stock exchange prediction.

Making prediction for a sector index by using past data of stocks which belong to that index can provide accurate forecasting for some indices if enough observation is provided in data set. Banking and tourism indices are forecasted well by the system. The forecasting can be improved by trying different combination of stocks' parameters like weighted average price and trading volume. Also forecasting can be enhanced by considering only séance 1 values for predicting séance 1 or séance 2.

There is a tradeoff between using past values and using new issued company's variables because missing value cannot be assigned in the past data for newly added company. If past data is needed to be used then new companies should be disregarded. In most cases using new companies and disregarding past data provided better results but the only way to find out best forecasting method is trial and error.

This approach can provide acceptable forecasts for some sector indices. But for certain time intervals the system might not provide that good results for the same index. Banking and tourism indices forecasts are good in most of the time intervals but in some time period the same system could not provide accurate results. Also some indices might not be forecasted accurately. Chemistry index could not be forecasted well by the system and most of the informatics index's forecasts are poor estimations. It might be related with sector and stocks characteristics. Again the best way to find if the sector index is applicable for a certain sector is trial and error method.

This study forecasted closing value of banking and tourism, sector indices of Istanbul Stock Exchanges accurately by mastering past data using neural networks. Also moderate forecasts are provided for food and informatics indices. This approach can be expanded by using technical and fundamental variables in data set. This approach can also be used other country's sector indices.

# APPENDIX A: NEURAL NETWORK TESTS

Test 1: XTRZM HISTORICAL WITH CHANGE, WITH WAP

(from 1997-01-02 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR)

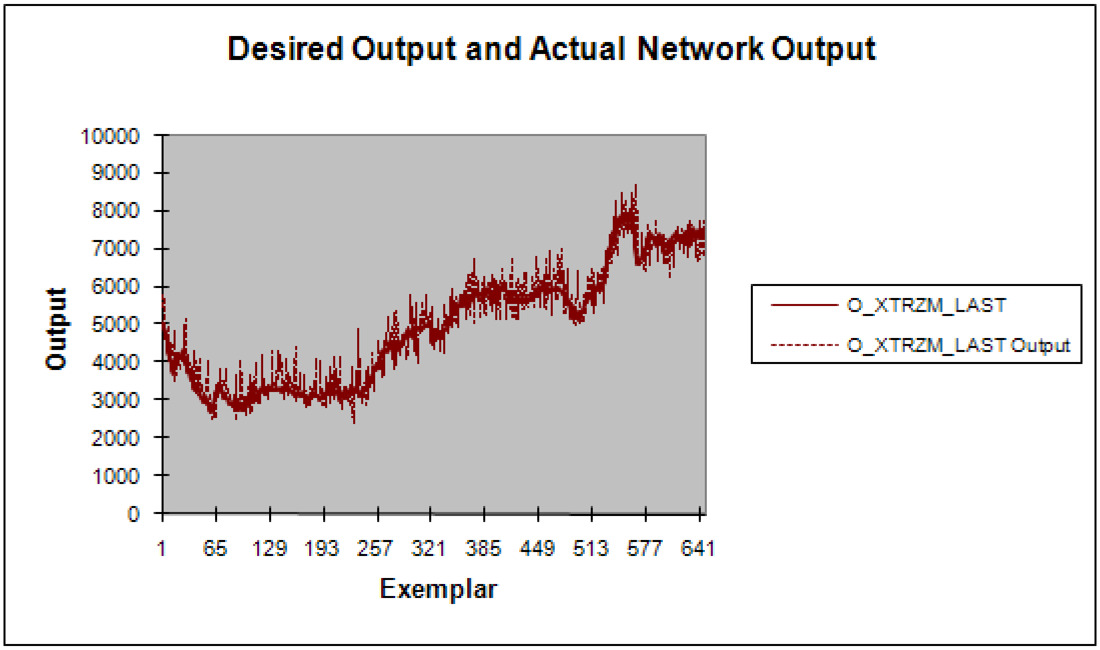


Figure 11: XTRZM séance 1,2 forecast with change with WAP – Step 1

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 171841.4821 |
| NMSE | 0.073070867 |
| MAE | 320.8190626 |
| Min Abs Error | 1.54997265 |
| Max Abs Error | 1527.600882 |
| R | 0.964419319 |

FAVORI added to index at August 8, 2000. TEKTU added to index August 10, 2008. MARTI added to index at January, 2 2009. They all are disregarded. Forecast is made by using historical data of MAALT and NTTUR. MAE has value of 320 which is less than %5 error for 641 séances.

Test 2: XTRZM HISTORICAL WITH CHANGE, WITH WAP

(from 2000-08-10 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR, TEKTU)

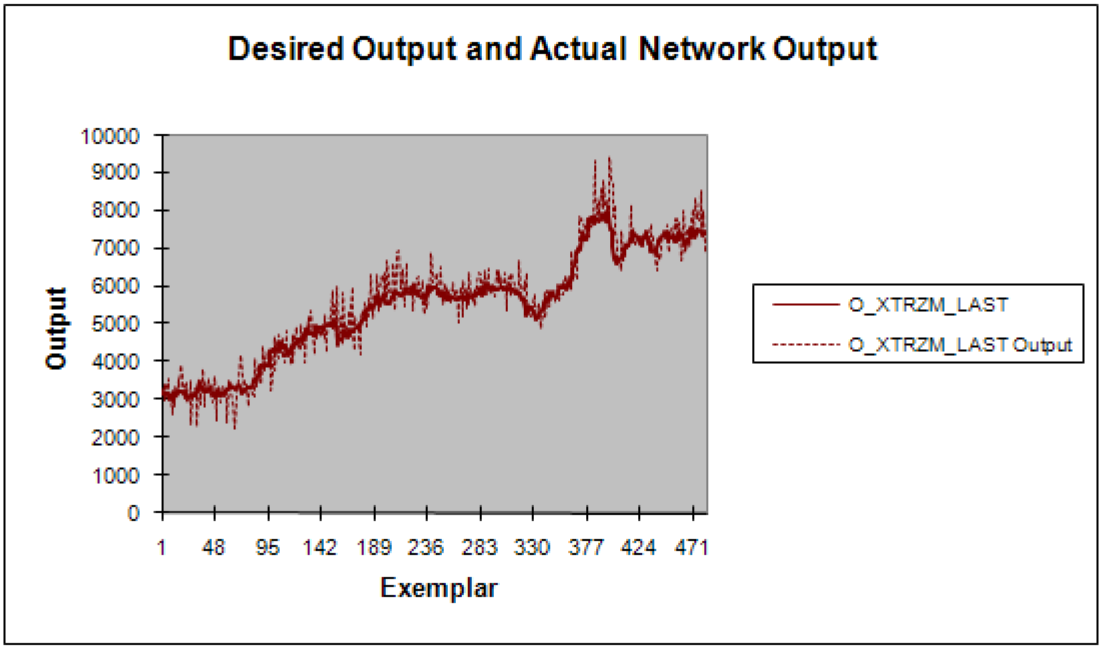


Figure 12: XTRZM séance 1,2 forecast with change with WAP - Step2

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 167181.1251 |
| NMSE | 0.084675354 |
| MAE | 307.4315135 |
| Min Abs Error | 0.180803422 |
| Max Abs Error | 1622.369677 |
| R | 0.967787081 |

Test 3: XTRZM HISTORICAL WITH CHANGE, WITH WAP

(from 2000-08-31 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR, TEKTU, FVORI)

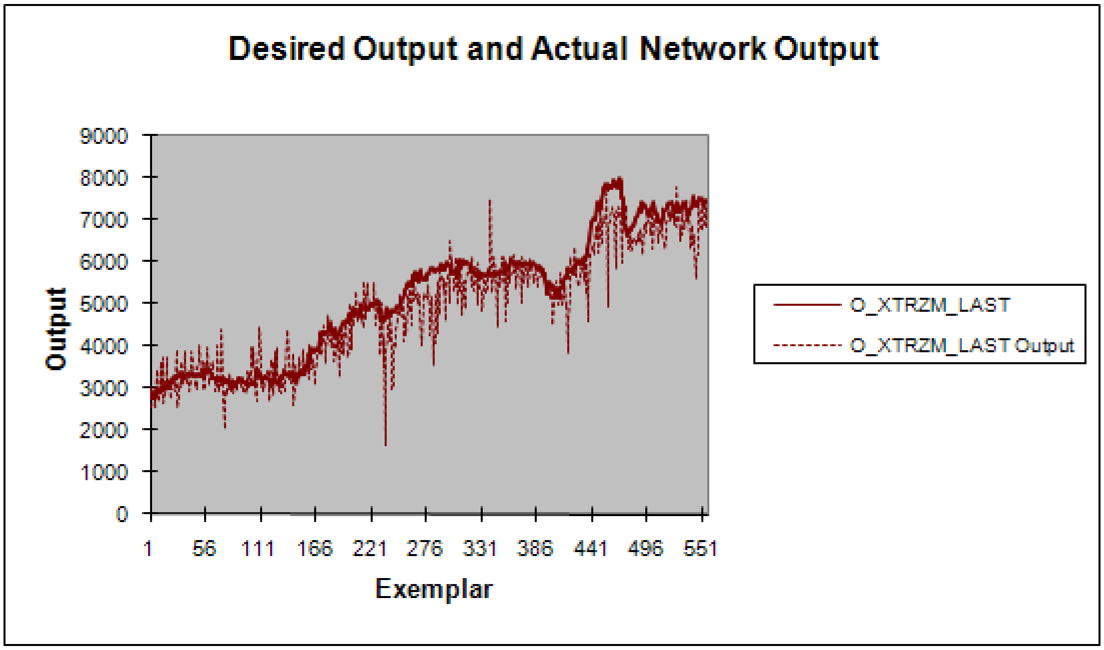


Figure 13: XTRZM séance 1,2 forecast with change with WAP - Step 3

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 327907.7758 |
| NMSE | 0.142005848 |
| MAE | 411.9885501 |
| Min Abs Error | 0.34177326 |
| Max Abs Error | 2987.925631 |
| R | 0.942281891 |

Test 4 – XTRZM HISTORICAL WITH CHANGE, WITH WAP

(from 2009-01-02 to 2009-12-30 for séance 1 and 2 with all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

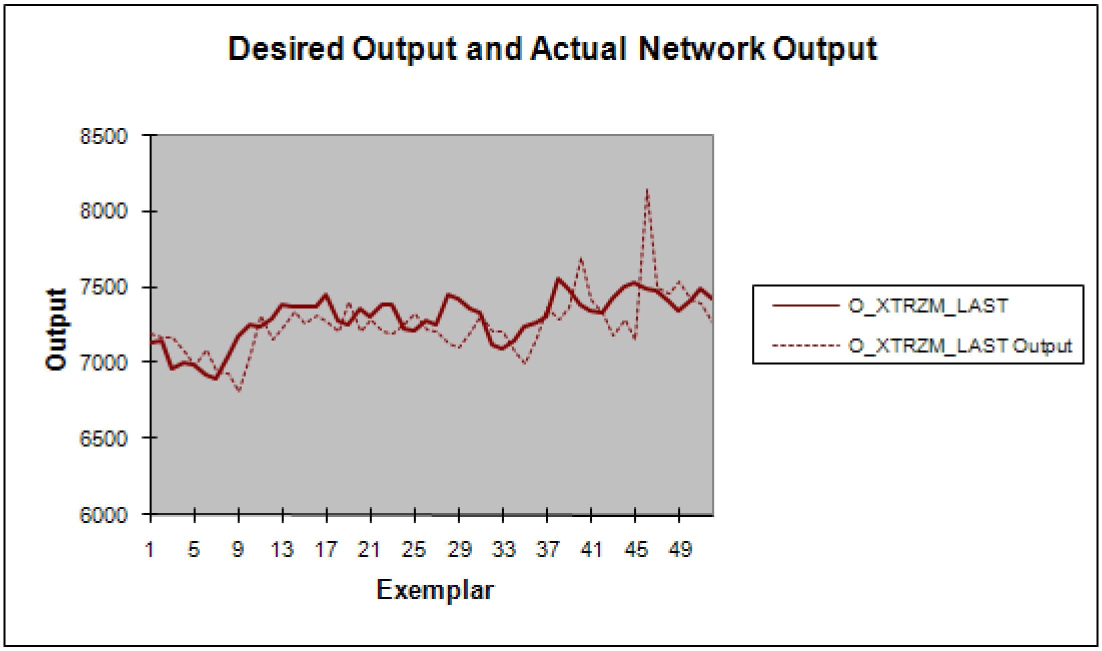


Figure 14: XTRZM séance 1,2 forecast with change with WAP - Step 4

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 34746.04443 |
| NMSE | 1.328363485 |
| MAE | 142.3444159 |
| Min Abs Error | 0.276197636 |
| Max Abs Error | 653.6789277 |
| R | 0.524257134 |

Test 5: XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP

(from 1997-01-02 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR)

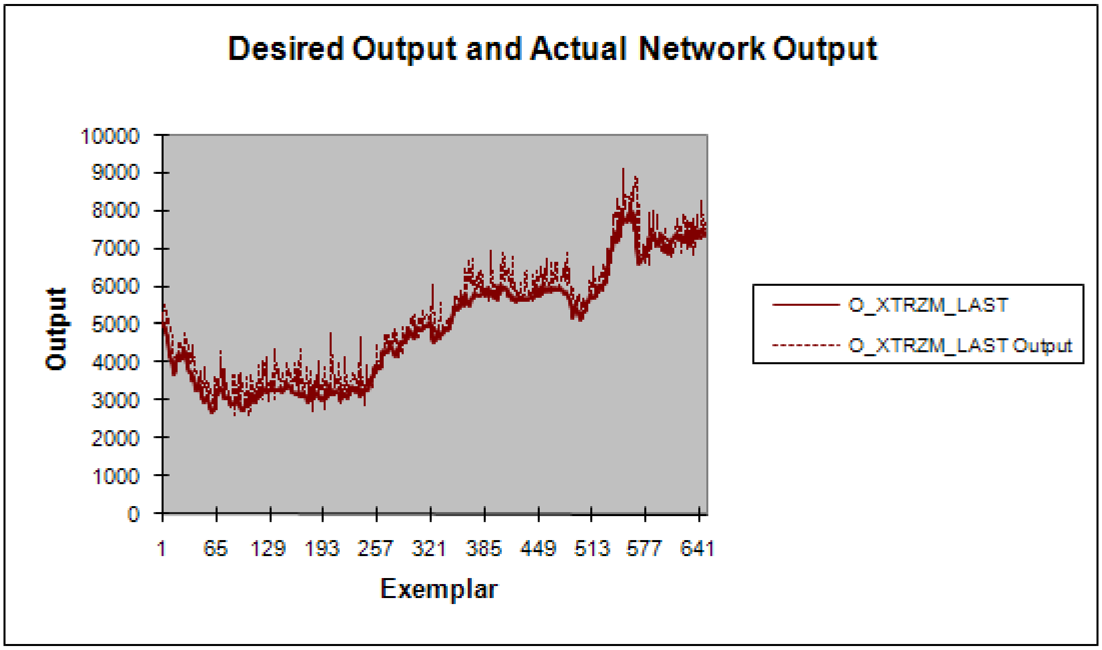


Figure 15: XTRZM séance 1,2 forecast with change without WAP - Step 1

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 159616.3414 |
| NMSE | 0.067976133 |
| MAE | 309.6156042 |
| Min Abs Error | 2.154318948 |
| Max Abs Error | 1436.17704 |
| R | 0.97848403 |

Test 6: XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP (from 2000-08-10 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR,TEKTU)

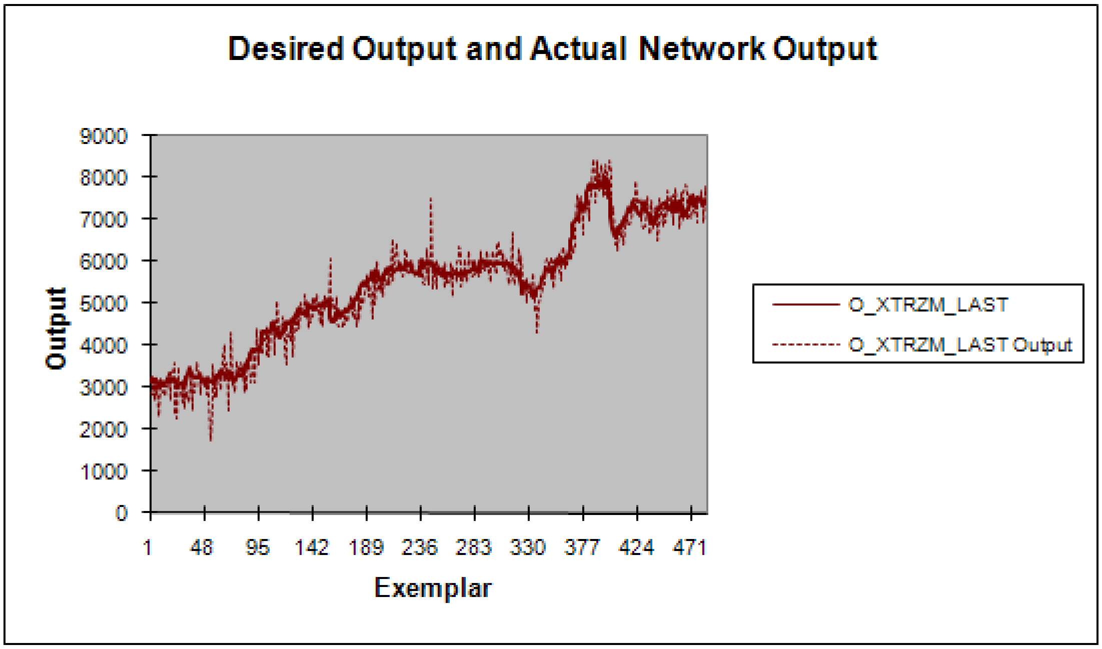


Figure 16: XTRZM séance 1,2 forecast with change without WAP - Step 2

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 125380.2928 |
| NMSE | 0.063279302 |
| MAE | 276.9574619 |
| Min Abs Error | 3.155590987 |
| Max Abs Error | 1491.87616 |
| R | 0.972518816 |

Test 7: XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP (from 2000-08-31 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR, TEKTU and FVORI)

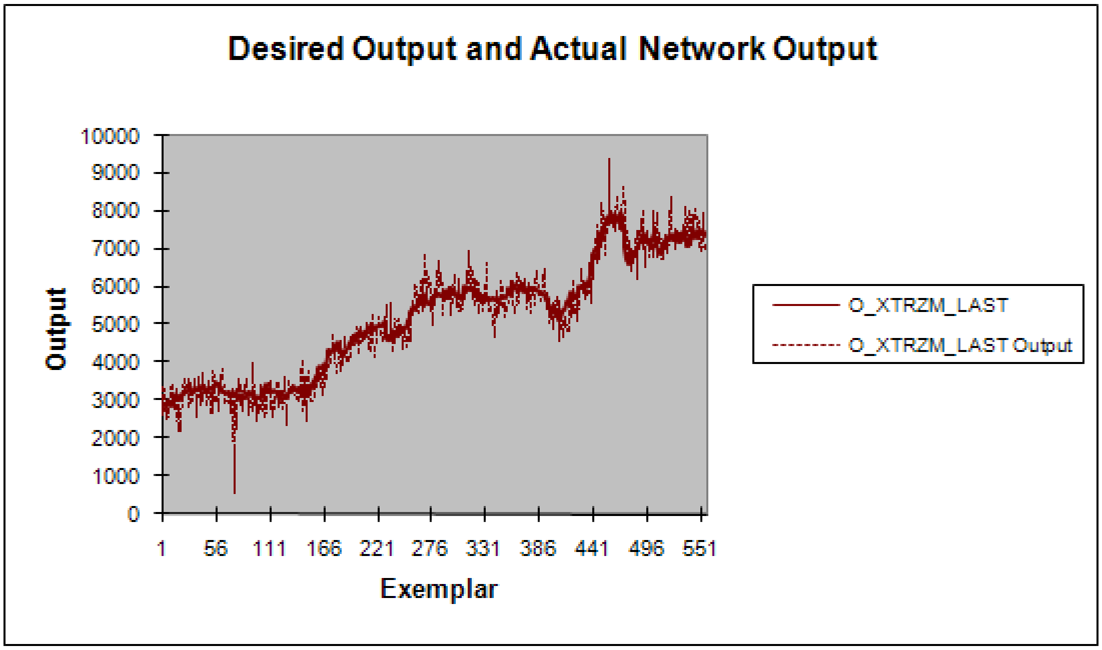


Figure 17: XTRZM séance 1,2 forecast with change without WAP - Step 3

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 164293.4131 |
| NMSE | 0.071149961 |
| MAE | 316.8371438 |
| Min Abs Error | 0.761764778 |
| Max Abs Error | 2572.040147 |
| R | 0.969855299 |

Test 8 – XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP (from 2009-01-02 to 2009-12-30 for séance 1 and 2 with all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

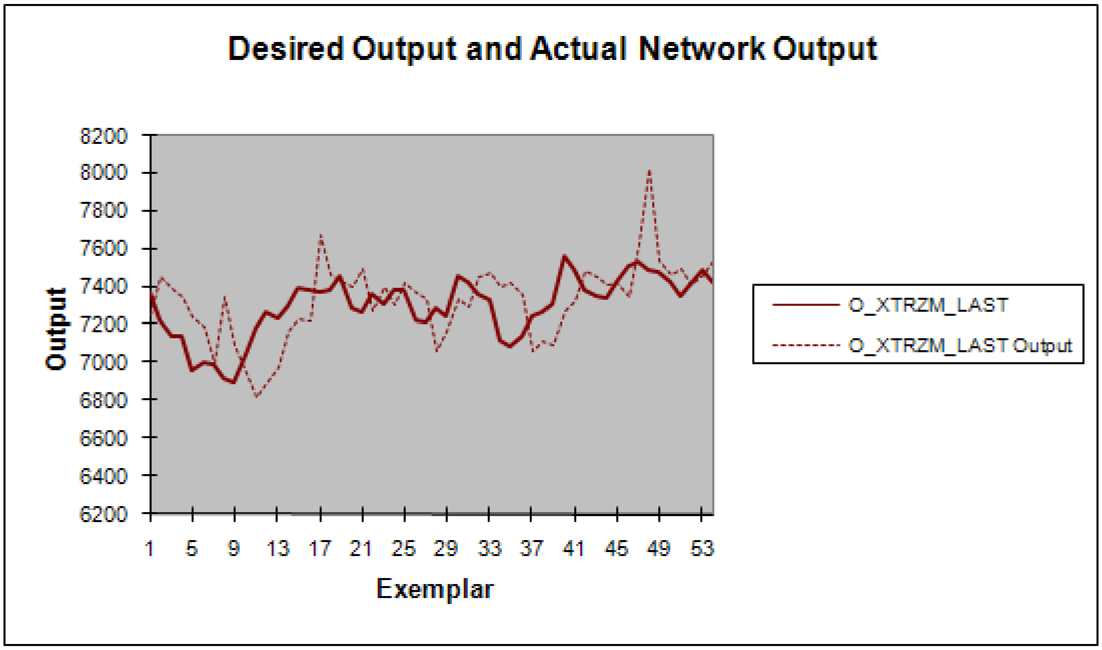


Figure 18: XTRZM séance 1,2 forecast with change without WAP - Step 4

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 39328.14875 |
| NMSE | 1.548200667 |
| MAE | 164.7718184 |
| Min Abs Error | 2.953803018 |
| Max Abs Error | 537.274282 |
| R | 0.453993337 |

Test 9: XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP
(from 1997-01-02 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR)

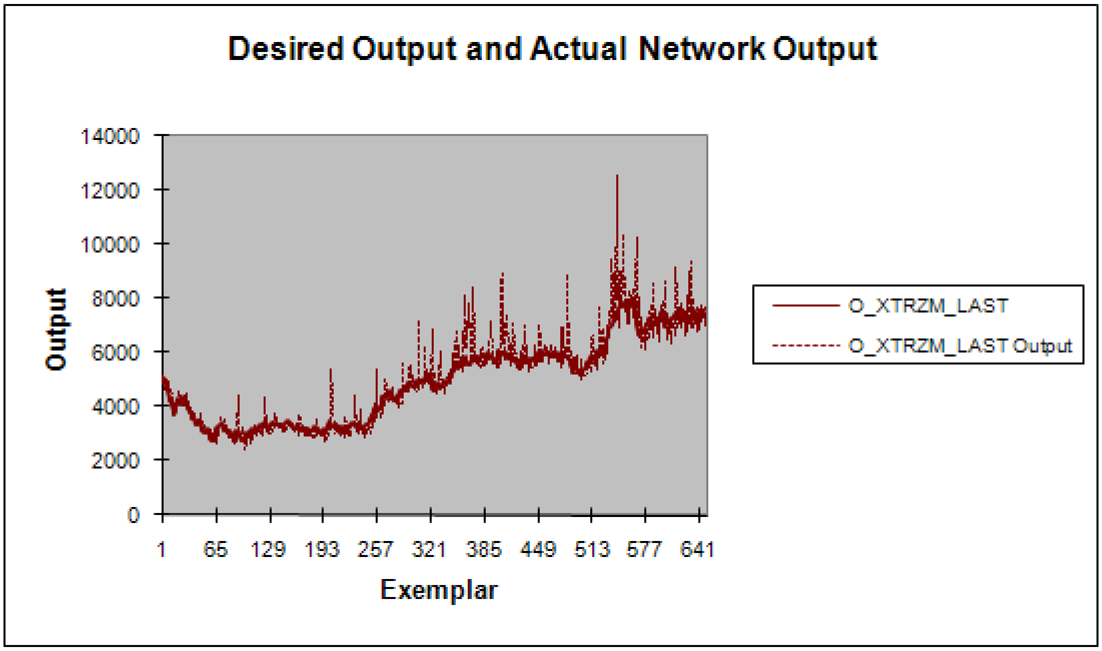


Figure 19: XTRZM séance 1,2 forecast without change without WAP - Step 1

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 366208.1744 |
| NMSE | 0.155957813 |
| MAE | 355.1477664 |
| Min Abs Error | 0.085121564 |
| Max Abs Error | 5309.081615 |
| R | 0.941188044 |

Test 10: XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP (from 2000-08-10 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR, TEKTU)

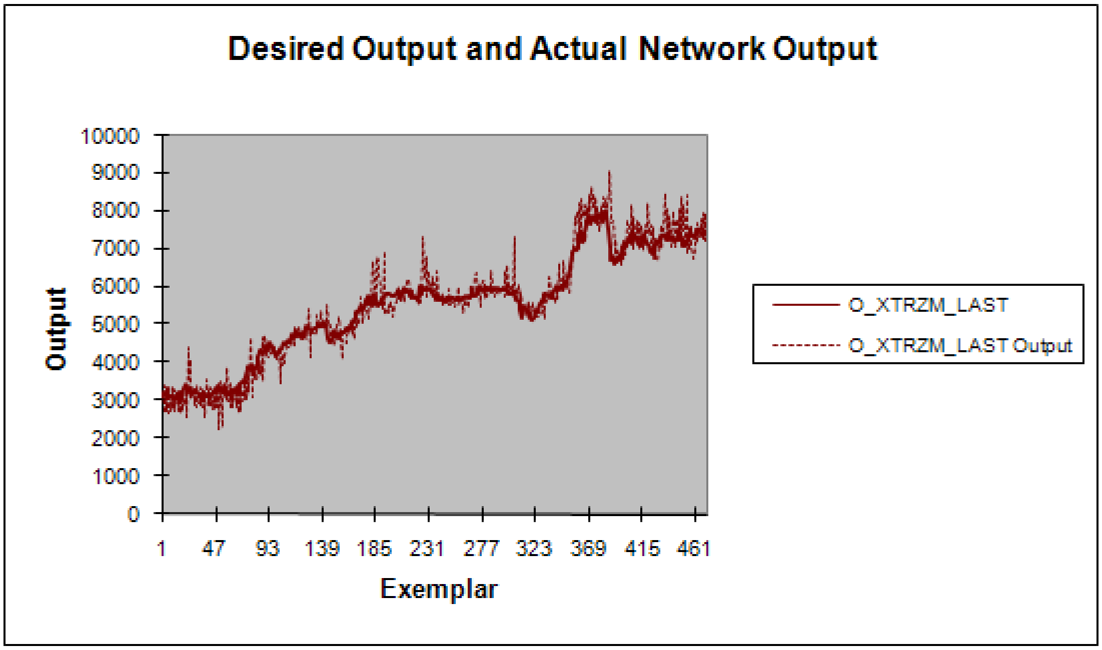


Figure 20: XTRZM séance 1,2 forecast without change without WAP - Step 2

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 164449.4658 |
| NMSE | 0.087817445 |
| MAE | 304.8307539 |
| Min Abs Error | 0.668494745 |
| Max Abs Error | 1511.817286 |
| R | 0.968433238 |

Test 11: XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP (from 2000-08-31 to 2009-12-30 for séance 1 and 2 with stocks MAALT, NTTUR, TEKTU, FVORI)

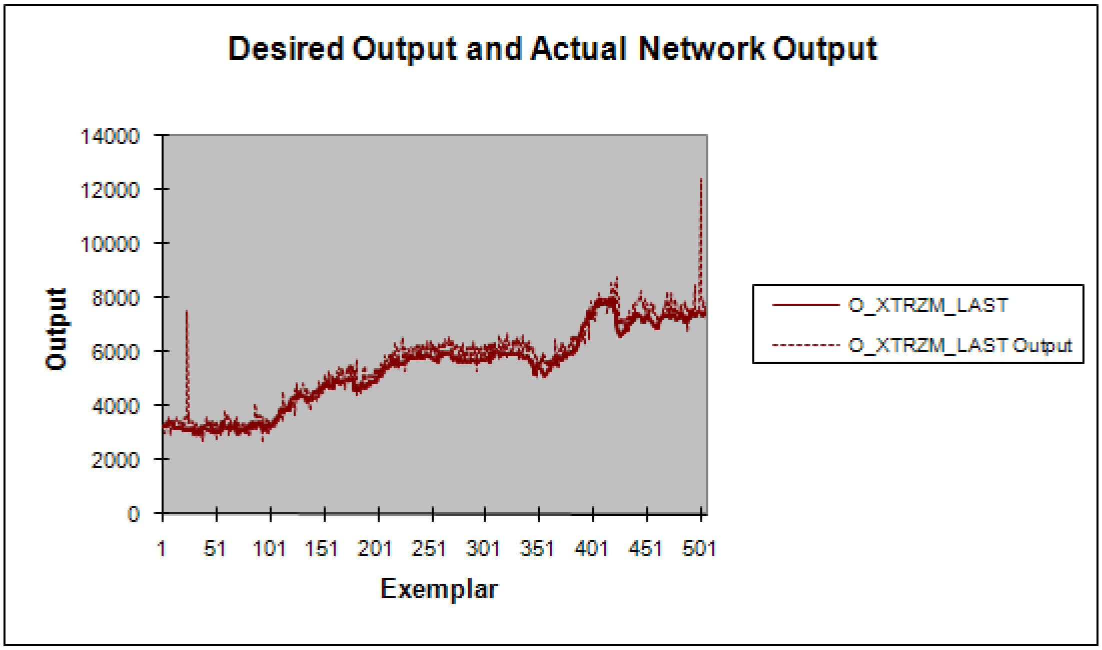


Figure 21: XTRZM séance 1,2 forecast without change without WAP - Step 3

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 224656.9031 |
| NMSE | 0.107463627 |
| MAE | 318.4933849 |
| Min Abs Error | 2.133661244 |
| Max Abs Error | 4897.195017 |
| R | 0.965584026 |

Test 12 – XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP (from 2009-01-02 to 2009-12-30 for séance 1 and 2 with all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

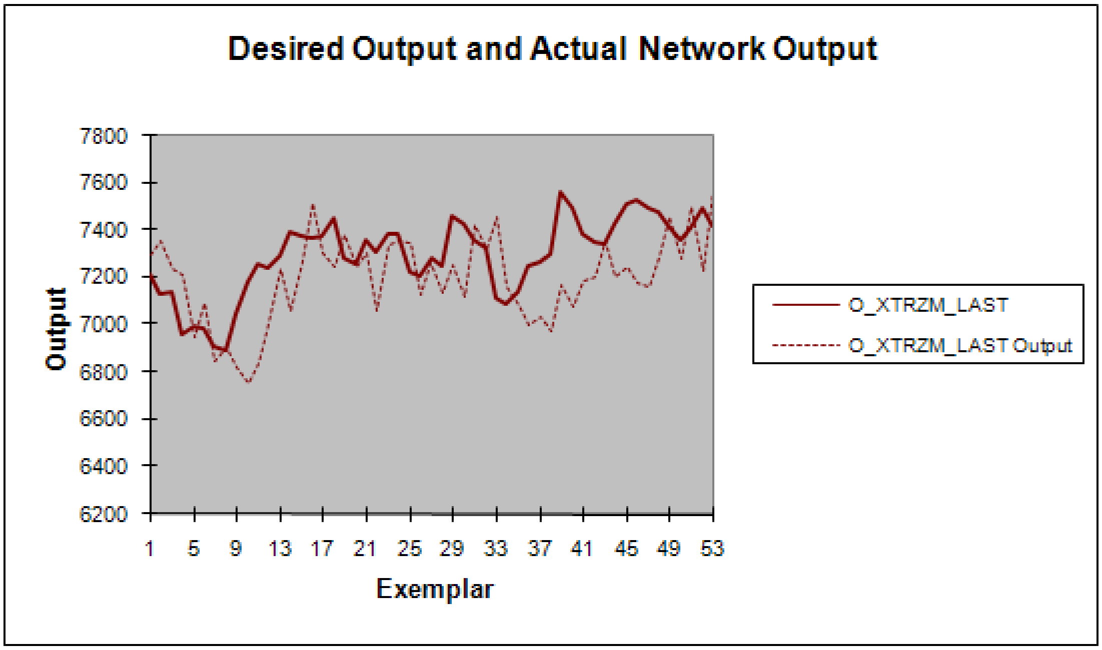


Figure 22: XTRZM séance 1,2 forecast without change without WAP - Step 4

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 43085.2402 |
| NMSE | 1.671551523 |
| MAE | 168.486998 |
| Min Abs Error | 5.997653361 |
| Max Abs Error | 425.7137218 |
| R | 0.431536495 |

Test 13: XTRZM HISTORICAL WITH CHANGE, WITH WAP

(from 1997-01-02 to 2009-12-30 for séance 2 with stocks MAALT, NTTUR)

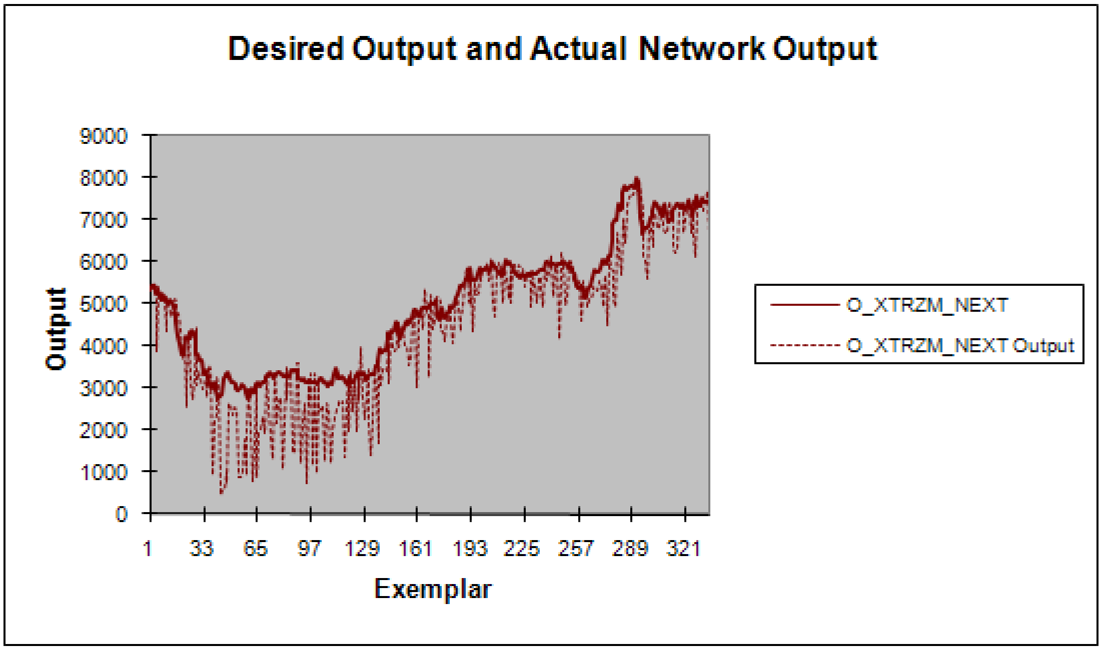


Figure 23: XTRZM séance 2 forecast with change with WAP - Step 1

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 699955.5159 |
| NMSE | 0.311312056 |
| MAE | 595.5383165 |
| Min Abs Error | 2.282344121 |
| Max Abs Error | 2631.188404 |
| R | 0.932906907 |

Test 14: XTRZM HISTORICAL WITH CHANGE, WITH WAP
(from 2000-08-31 to 2009-12-30 for séance 2 with stocks MAALT, NTTUR, TEKTU, FVORI)

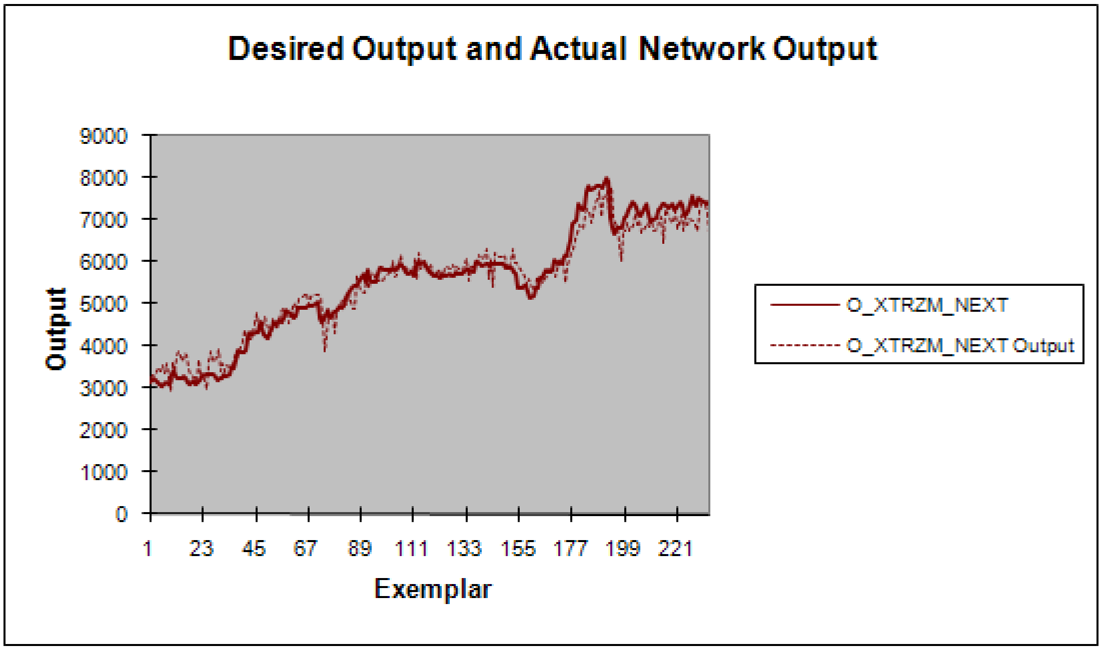


Figure 24: XTRZM séance 2 forecast with change with WAP - Step 2

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 100784.4772 |
| NMSE | 0.05405247 |
| MAE | 252.1422202 |
| Min Abs Error | 1.289887484 |
| Max Abs Error | 940.3662356 |
| R | 0.978698005 |

Test 15 – XTRZM HISTORICAL WITH CHANGE, WITH WAP

(from 2009-01-02 to 2009-12-30 for séance 2 with all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

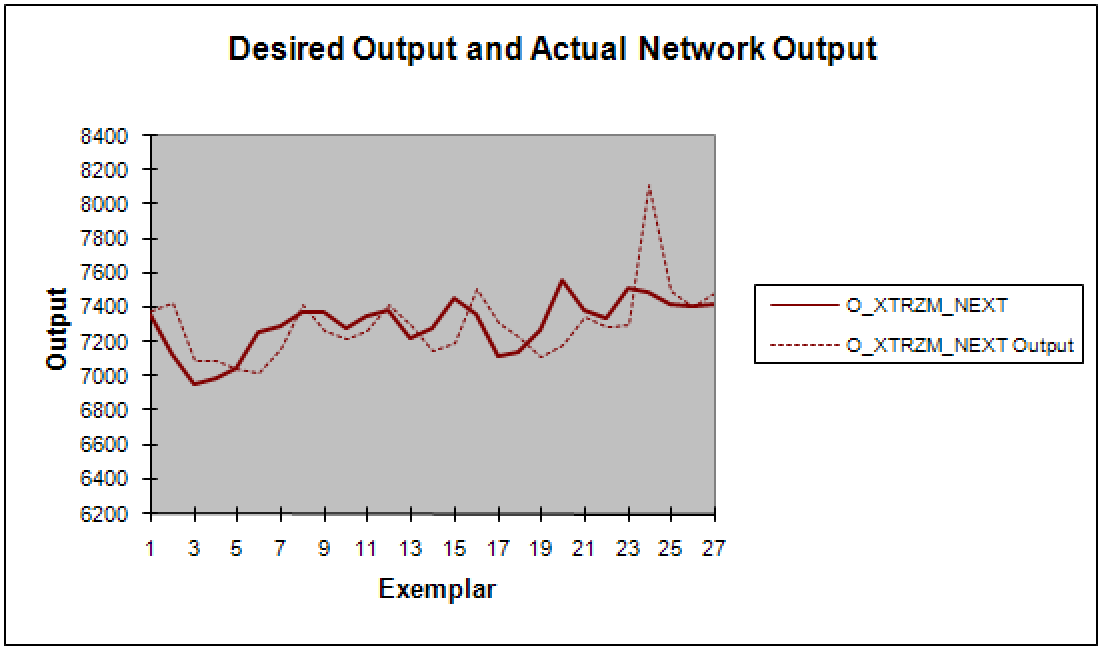


Figure 25: XTRZM séance 2 forecast with change with WAP - Step 3

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 37015.57615 |
| NMSE | 1.607001002 |
| MAE | 139.7141887 |
| Min Abs Error | 4.650300688 |
| Max Abs Error | 629.772787 |
| R | 0.478925939 |

Test 16: XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP
(from 1997-01-02 to 2009-12-30 for séance 2 with stocks MAALT, NTTUR)

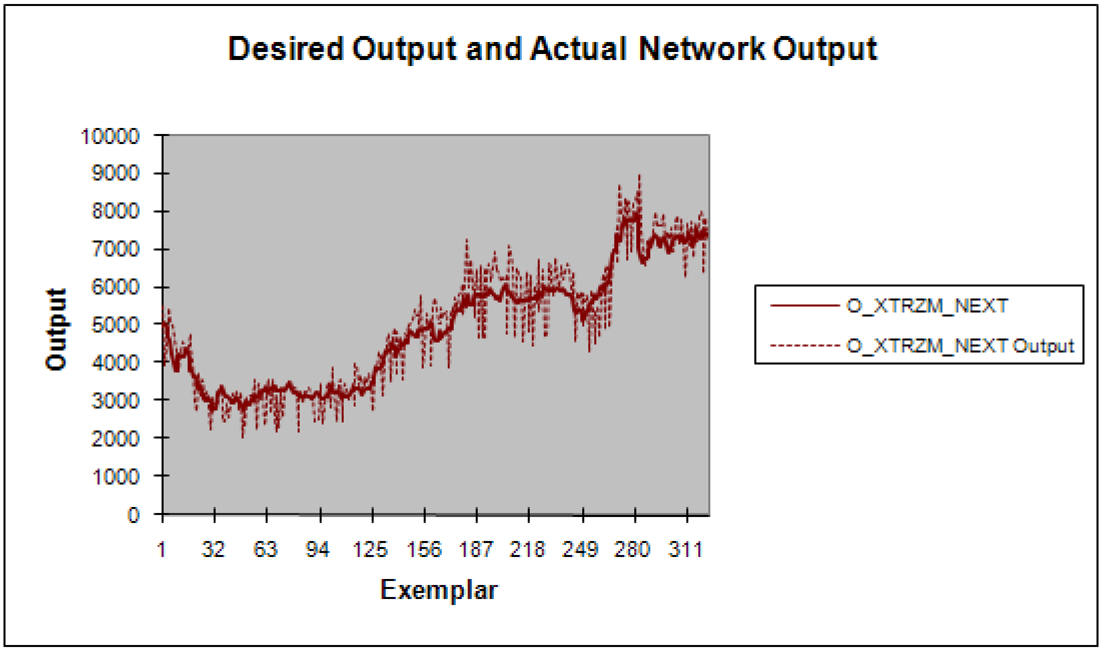


Figure 26: XTRZM séance 2 forecast with change without WAP - Step 1

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 332124.3398 |
| NMSE | 0.143092273 |
| MAE | 464.4954772 |
| Min Abs Error | 1.488718499 |
| Max Abs Error | 1938.46376 |
| R | 0.943429784 |

Test 17: XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP (from 2000-08-31 to 2009-12-30 for séance 2 with stocks MAALT, NTTUR, TEKTU, FVORI)

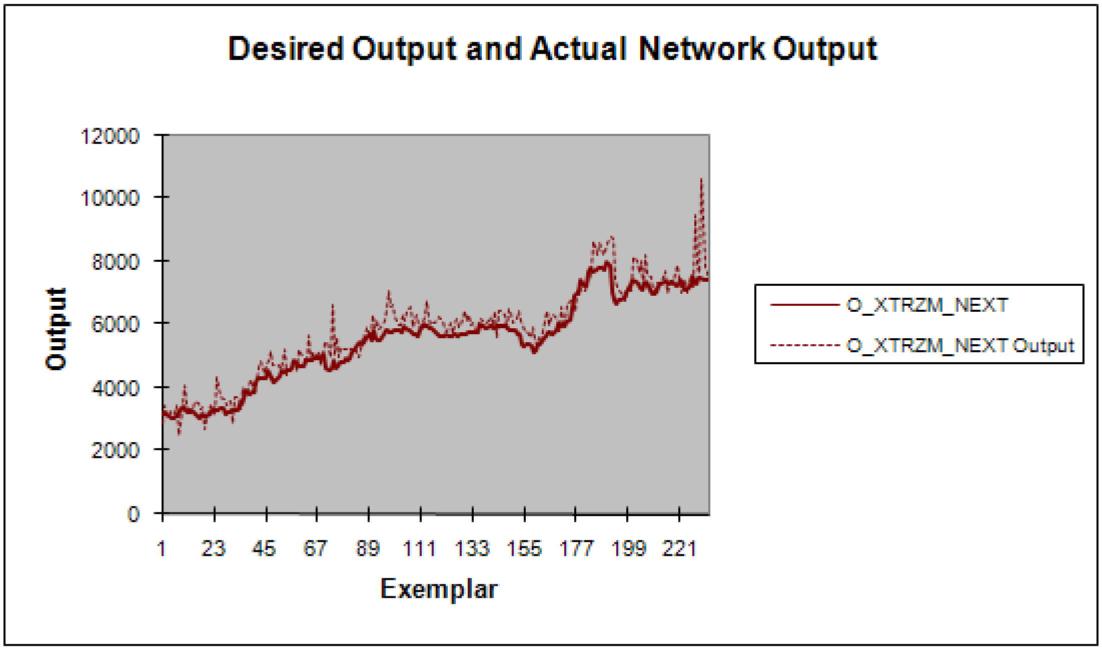


Figure 27: XTRZM séance 2 forecast with change without WAP - Step 2

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 254964.2033 |
| NMSE | 0.137972025 |
| MAE | 368.0084487 |
| Min Abs Error | 0.518103216 |
| Max Abs Error | 3139.765523 |
| R | 0.960998176 |

Test 18 – XTRZM HISTORICAL WITH CHANGE, WITHOUT WAP (from 2009-01-02 to 2009-12-30 for séance 2 with all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

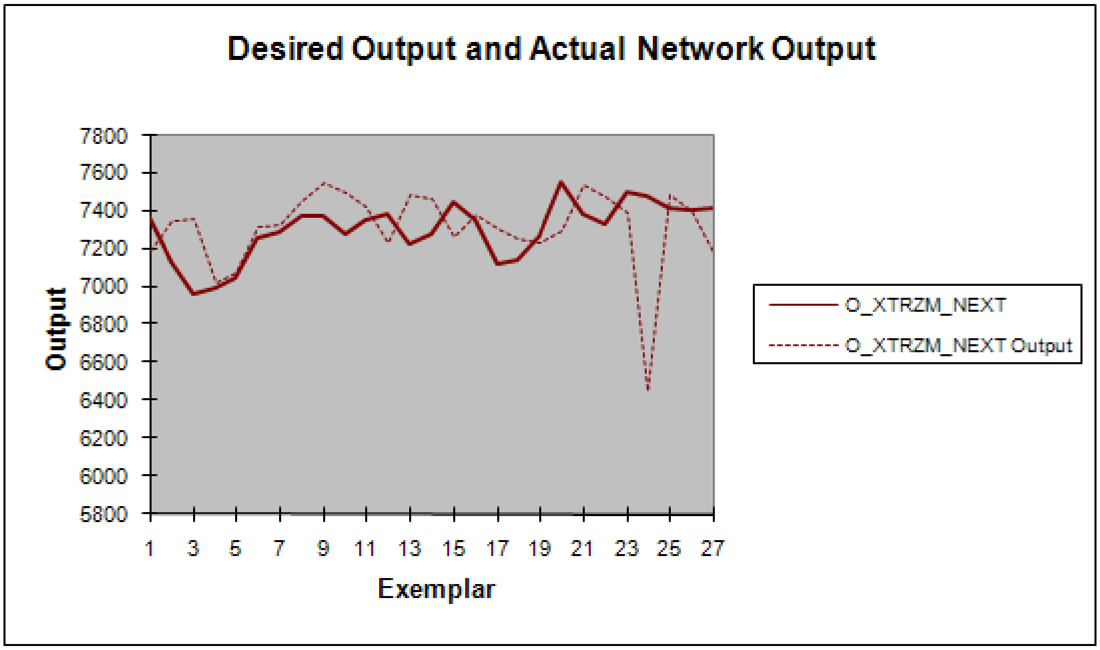


Figure 28: XTRZM séance 2 forecast with change without WAP - Step 3

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 66881.83584 |
| NMSE | 2.903620271 |
| MAE | 172.0839098 |
| Min Abs Error | 9.381052774 |
| Max Abs Error | 1037.183553 |
| r | 0.03272845 |

Test 19: XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP (from 1997-01-02 to 2009-12-30 for séance 2 with stocks MAALT, NTTUR)

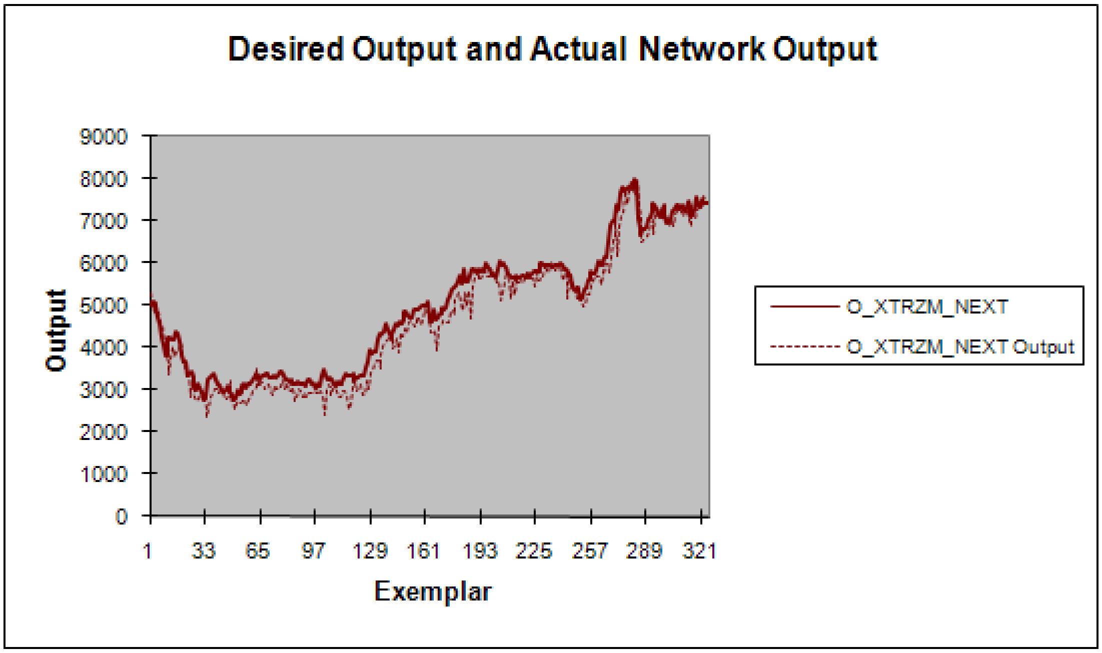


Figure 29: XTRZM séance 2 forecast without change without WAP - Step 1

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 98561.20156 |
| NMSE | 0.042593781 |
| MAE | 249.1689275 |
| Min Abs Error | 0.243495549 |
| Max Abs Error | 1071.214692 |
| r | 0.990471716 |

Test 20: XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP (from 2000-08-31 to 2009-12-30 for séance 2 with stocks MAALT, NTTUR, TEKTU, FVORI)

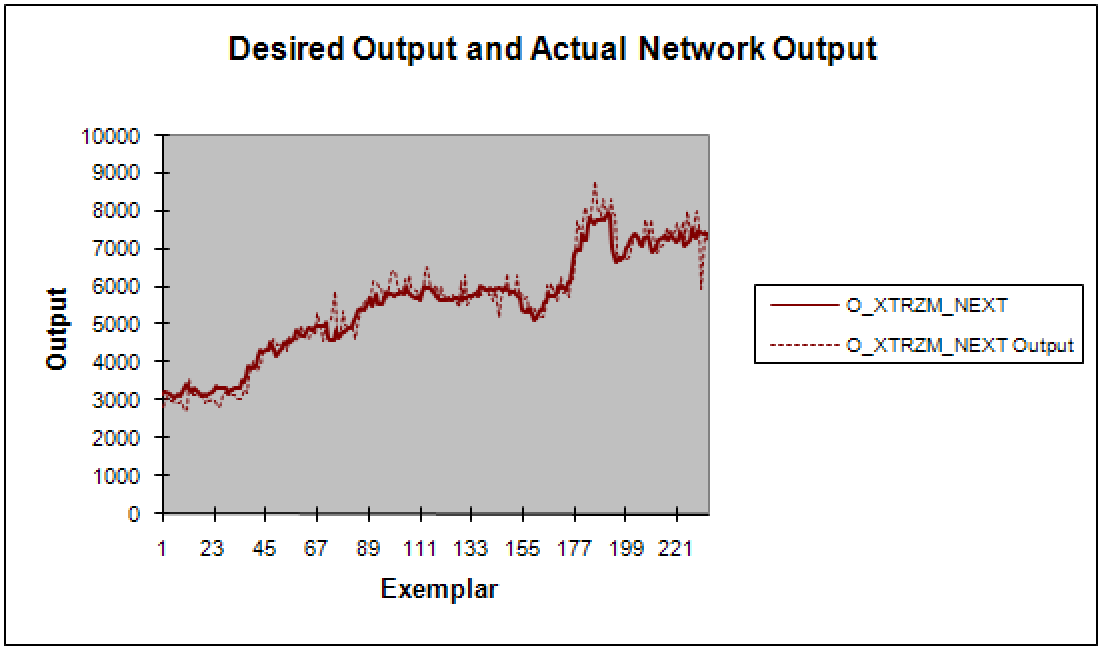


Figure 30: XTRZM séance 2 forecast without change without WAP - Step 2

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 108186.246 |
| NMSE | 0.058022168 |
| MAE | 236.2048138 |
| Min Abs Error | 1.007541448 |
| Max Abs Error | 1534.511291 |
| r | 0.978575175 |

Test 21 – XTRZM HISTORICAL WITHOUT CHANGE, WITHOUT WAP (from 2009-01-02 to 2009-12-30 for séance 2 with all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

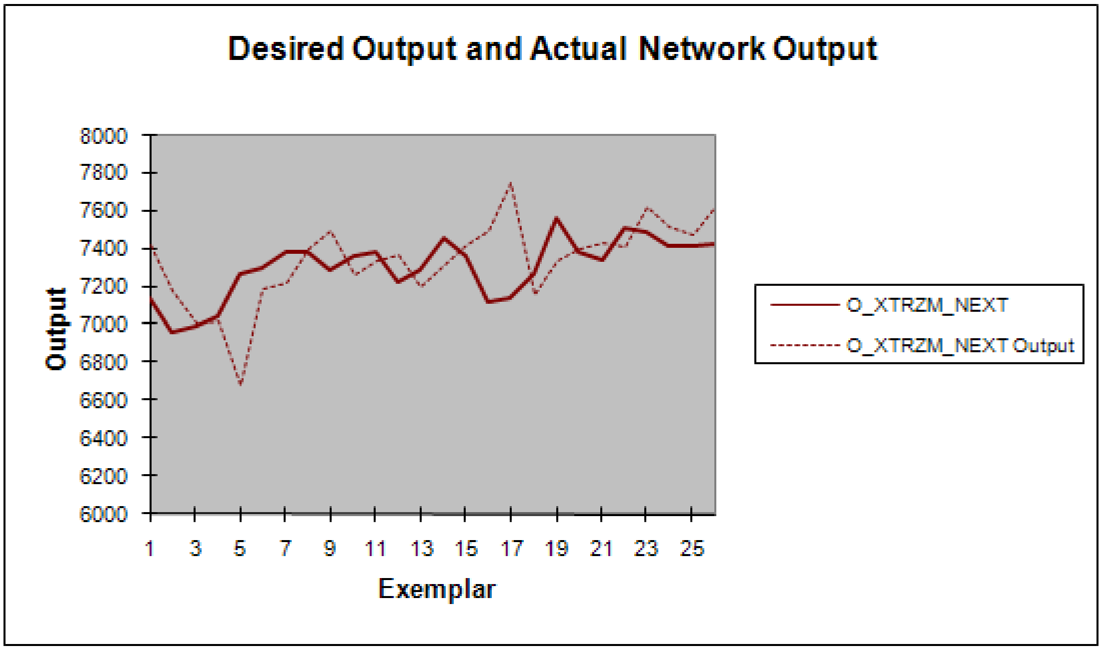


Figure 31: XTRZM séance 2 forecast without change without WAP - Step 3

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 49006.34247 |
| NMSE | 2.063340501 |
| MAE | 161.9785266 |
| Min Abs Error | 16.37860924 |
| Max Abs Error | 607.9488854 |
| r | 0.344592694 |

Test 22: XTRZM HISTORICAL WITHOUT CHANGE, WITH WAP (from 1997-01-02 to 2009-12-30 for séance 1 with stocks MAALT, NTTUR)

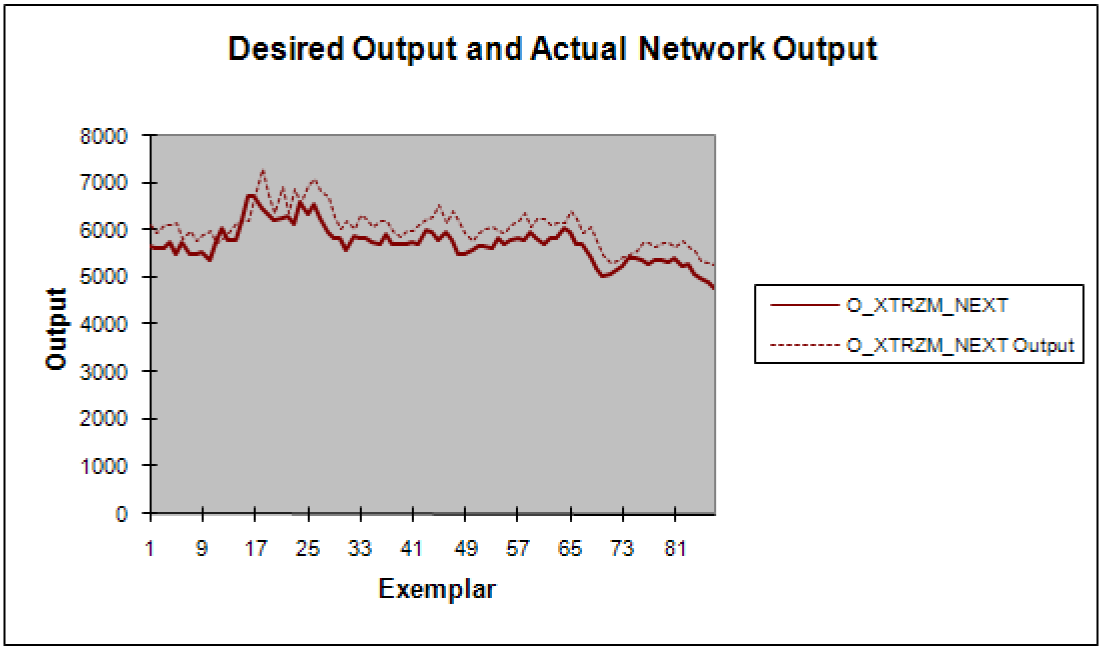


Figure 32: XTRZM séance 2 forecast without change with WAP - Step 1

| *Performance* | *O_XTRZM_NEXT* |
|---|---|
| MSE | 167699.2434 |
| NMSE | 1.08095924 |
| MAE | 361.8166896 |
| Min Abs Error | 7.375328413 |
| Max Abs Error | 812.2354139 |
| r | 0.84187459 |

Test 23: XTRZM HISTORICAL WITHOUT CHANGE, WITH WAP (from 2000-08-31 to 2009-12-30 for séance 1 with stocks MAALT, NTTUR, TEKTU, FVORI)

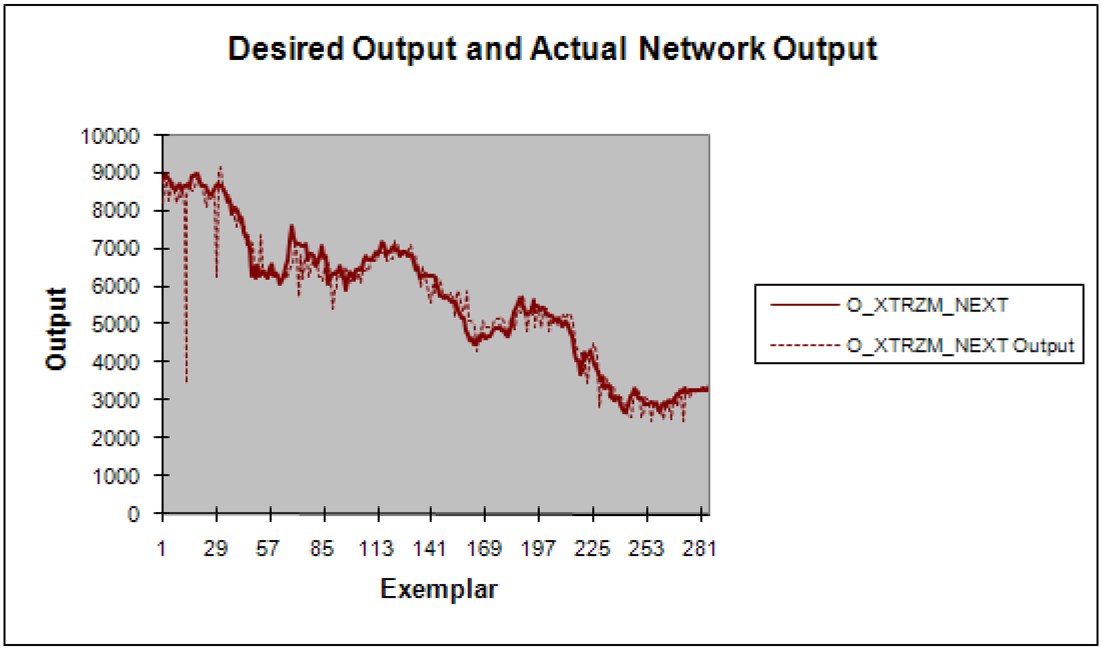


Figure 33: XTRZM séance 2 forecast without change with WAP - Step 2

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 214949.6358 |
| NMSE | 0.067881562 |
| MAE | 260.7599095 |
| Min Abs Error | 1.0487935 |
| Max Abs Error | 5195.227013 |
| r | 0.966696649 |

Test 24 – XTRZM HISTORICAL WITHOUT CHANGE, WITH WAP (from 2009-01-02 to 2009-12-30 for séance 1 With all stocks in XTRZM index MAALT, FVORI, MARTI, NTTUR, TEKTU)

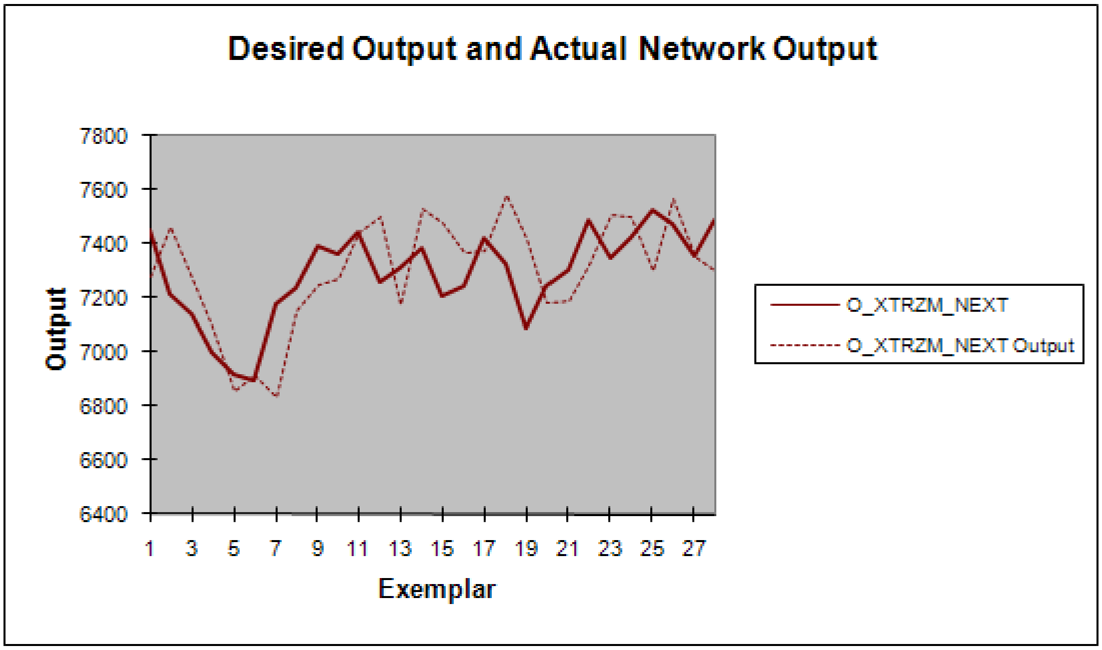


Figure 34: XTRZM séance 2 forecast without change with WAP - Step 3

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 28928.91573 |
| NMSE | 1.050221092 |
| MAE | 144.0425234 |
| Min Abs Error | 1.991754228 |
| Max Abs Error | 346.3415851 |
| r | 0.584113686 |

Test 25: XTRZM HISTORICAL WITHOUT CHANGE, WITH WAP (from 1997-01-02 to 2009-12-30 for séance 1 with stocks MAALT, NTTUR)

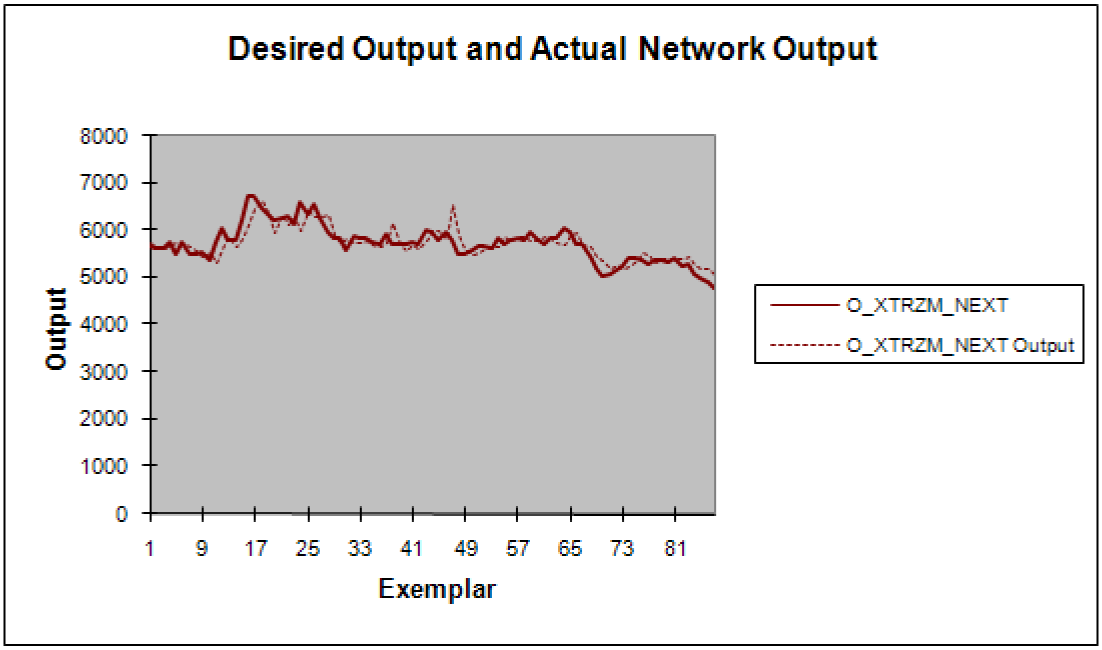


Figure 35: XTRZM séance 1 forecast without change with WAP - Step 1

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 48560.20357 |
| NMSE | 0.313010361 |
| MAE | 165.8631255 |
| Min Abs Error | 5.135535863 |
| Max Abs Error | 771.344717 |
| r | 0.828931037 |

Test 26: XTRZM HISTORICAL WITHOUT CHANGE, WITH WAP (from 2000-08-31 to 2009-12-30 for séance 1 with stocks MAALT, NTTUR, TEKTU, FVORI)

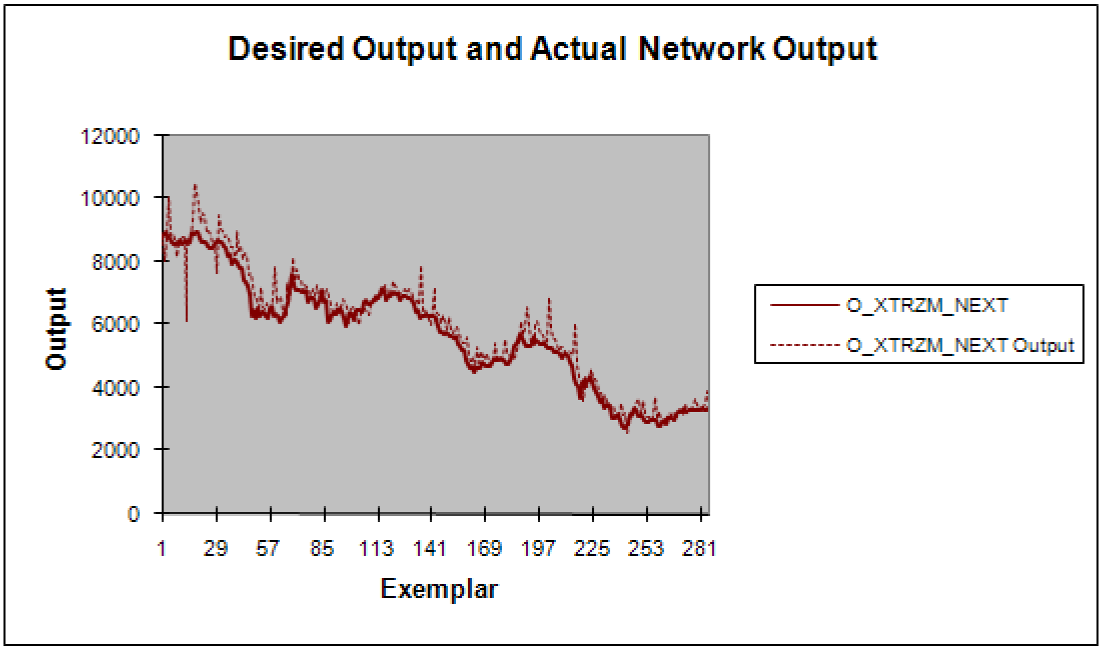


Figure 36: XTRZM séance 1 forecast without change with WAP - Step 2

| Performance | O_XTRZM_NEXT |
|---|---|
| MSE | 202400.936 |
| NMSE | 0.063918655 |
| MAE | 309.8104701 |
| Min Abs Error | 1.048017627 |
| Max Abs Error | 2541.876664 |
| r | 0.977171116 |

Test 27: XKMY HISTORICAL WITH CHANGE, WITH WAP (from 1997-01-02 to 2009-12-31 for séance 1 and 2 with 16 Stocks)

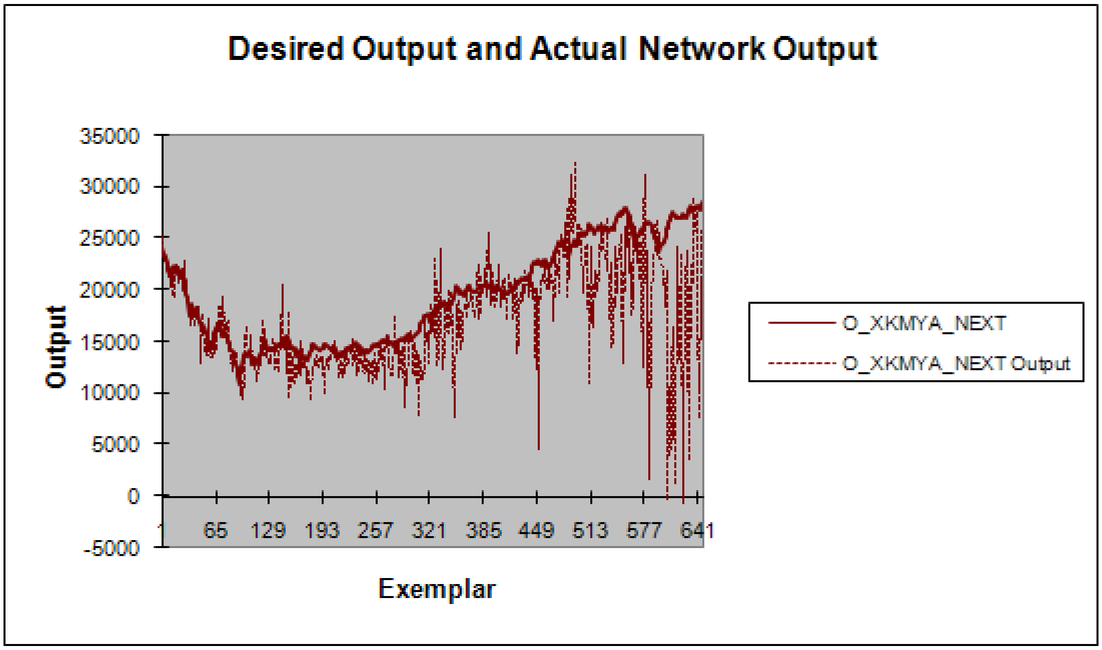


Figure 37: XKMY séance 1,2 forecast with change with WAP - Step 1

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 25702461.1 |
| NMSE | 1.080121563 |
| MAE | 2898.444899 |
| Min Abs Error | 8.326875501 |
| Max Abs Error | 28339.97471 |
| r | 0.586295079 |

Test 28: XKMY HISTORICAL WITH CHANGE, WITH WAP (from 1999-11-03 to 2009-12-31 for séance 1 and 2 with 17 Stocks)

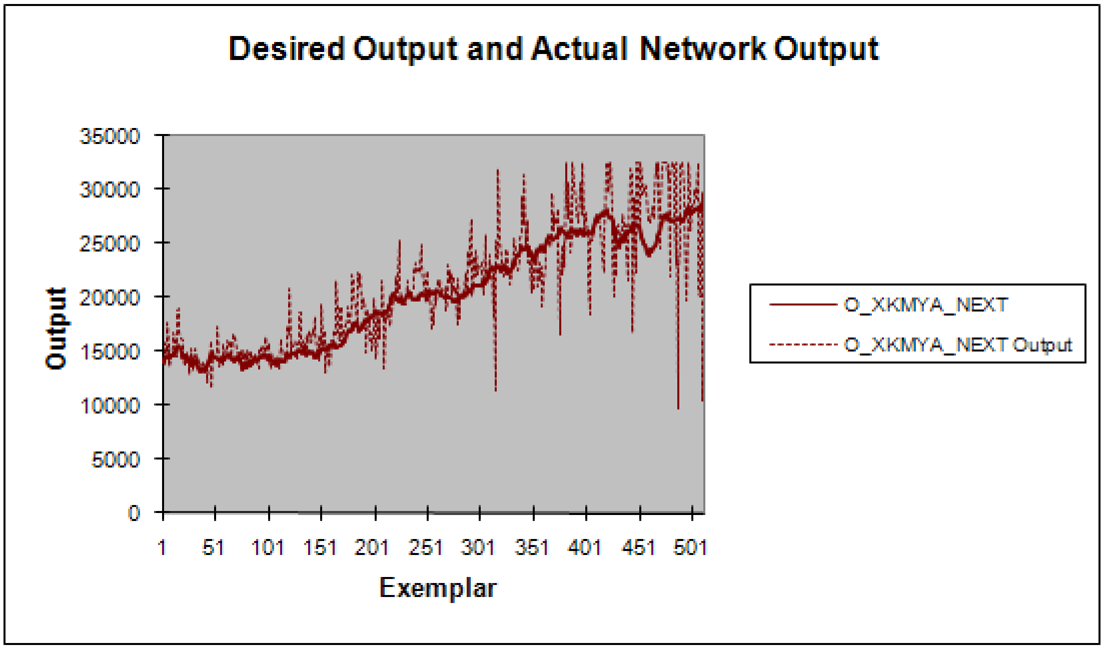


Figure 38: XKMY séance 1,2 forecast with change with WAP - Step 2

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 8583463.073 |
| NMSE | 0.354561929 |
| MAE | 1968.567369 |
| Min Abs Error | 1.86872918 |
| Max Abs Error | 18255.14414 |
| r | 0.861716322 |

Test 29: XKMY HISTORICAL WITH CHANGE, WITH WAP (from 2001-01-02 to 2009-12-31 for séance 1 and 2 with 20 Stocks)

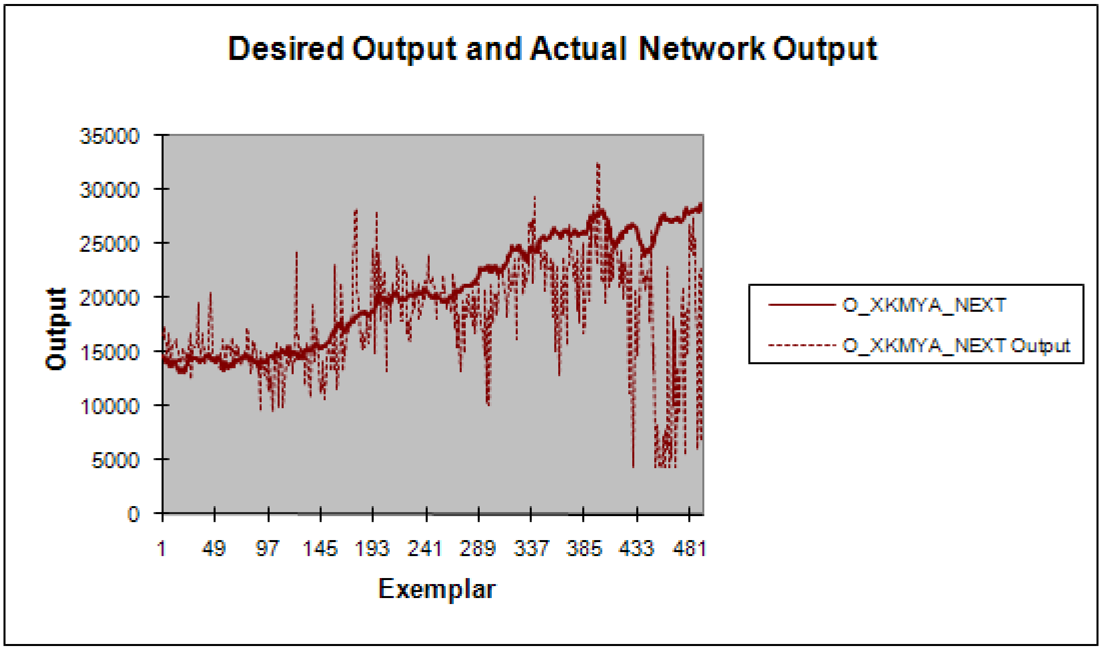


Figure 39: XKMY séance 1,2 forecast with change with WAP - Step 3

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 36643156.11 |
| NMSE | 1.533323898 |
| MAE | 3676.247024 |
| Min Abs Error | 1.486198016 |
| Max Abs Error | 23255.28167 |
| r | 0.366739563 |

Test 30: XGIDA HISTORICAL WITH CHANGE, WITH WAP (from 1997-01-02 to 2009-12-31 for séance 1 and 2 with 11 Stocks)

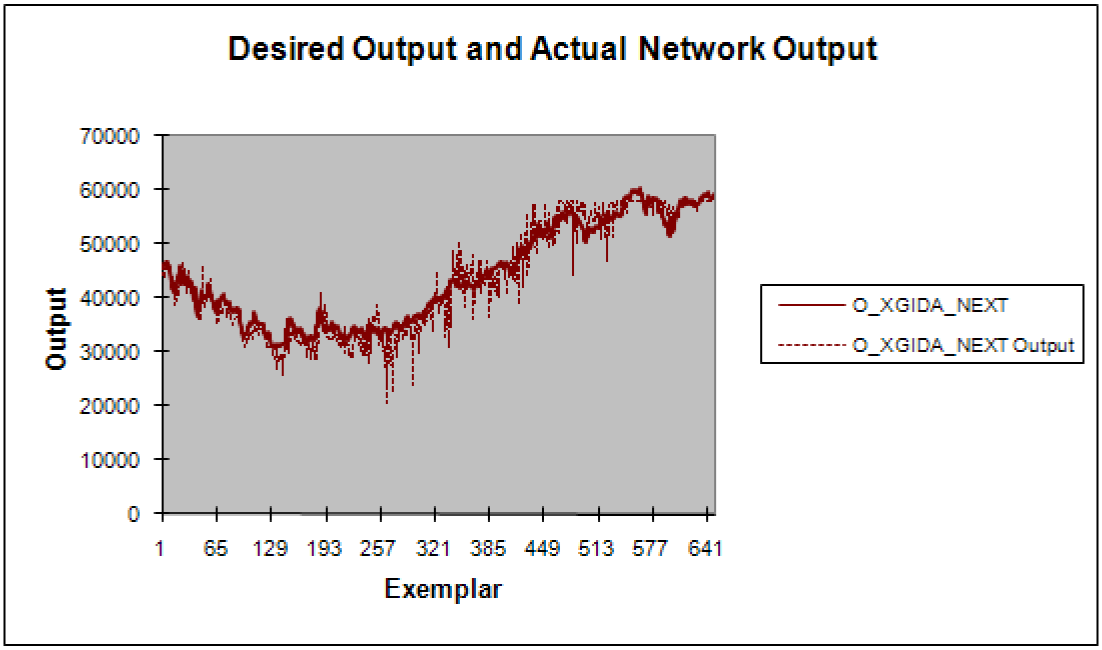


Figure 40: XGIDA séance 1,2 forecast with change with WAP - Step 1

| *Performance* | *O_XGIDA_NEXT* |
|---|---|
| MSE | 6739221.928 |
| NMSE | 0.079525902 |
| MAE | 1916.101266 |
| Min Abs Error | 18.46612099 |
| Max Abs Error | 13398.54979 |
| r | 0.970727707 |

Test 31: XGIDA HISTORICAL WITH CHANGE, WITH WAP (from 2000-08-11 to 2009-12-31 for séance 1 and 2 with 18 Stocks)

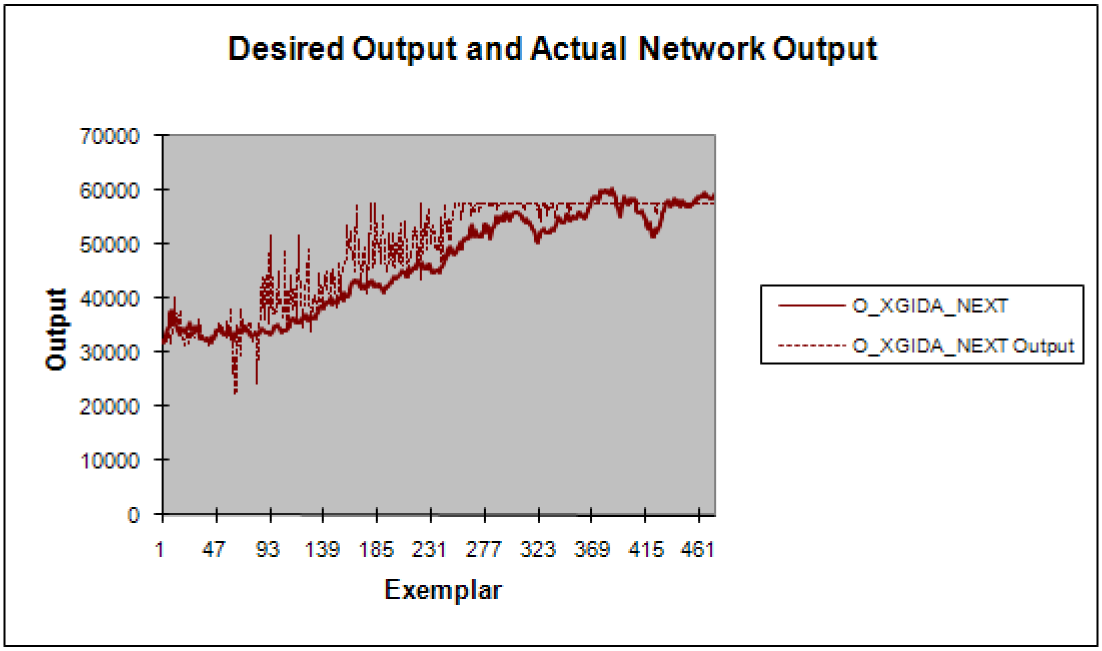


Figure 41: XGIDA séance 1,2 forecast with change with WAP - Step 2

| Performance | O_XGIDA_NEXT |
|---|---|
| MSE | 20766668.61 |
| NMSE | 0.239959528 |
| MAE | 3400.340346 |
| Min Abs Error | 4.224488931 |
| Max Abs Error | 18385.42303 |
| r | 0.924995982 |

Test 32: XELKT HISTORICAL WITH CHANGE, WITH WAP (from 2000-07-07 to 2009-12-31 for séance 1 and 2 with 4 Stocks)

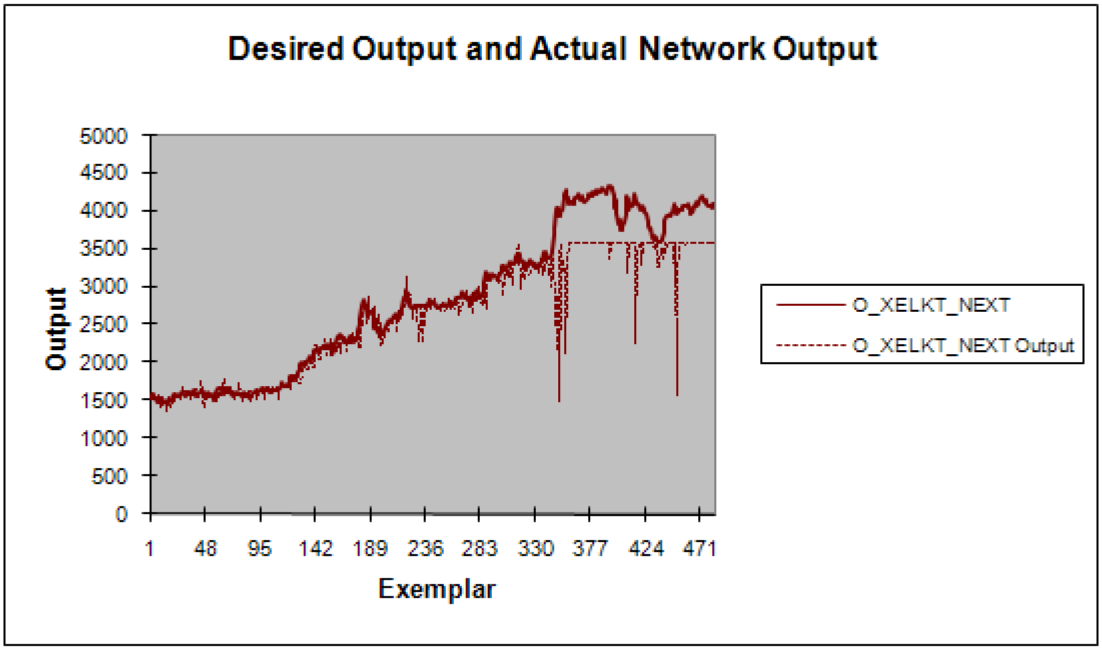


Figure 42: XELKT séance 1,2 forecast with change with WAP

| Performance | O_XELKT_NEXT |
| --- | --- |
| MSE | 145860.5223 |
| NMSE | 0.160351711 |
| MAE | 221.3362889 |
| Min Abs Error | 0.037060484 |
| Max Abs Error | 2485.257072 |
| r | 0.949303207 |

Test 33: XBLSM HISTORICAL WITH CHANGE, WITH WAP (from 2000-11-02 to 2009-12-31 for séance 1 and 2 with 6 Stocks)

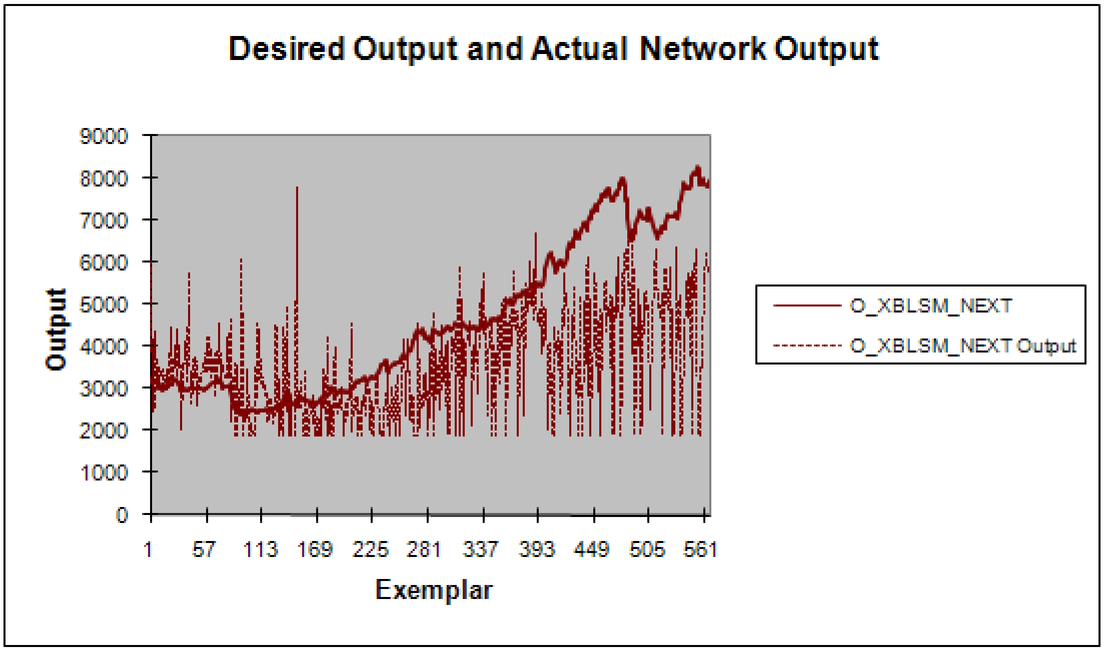


Figure 43: XBLSM séance 1,2 forecast with change with WAP Step 1

| Performance | O_XBLSM_NEXT |
|---|---|
| MSE | 3725097.09 |
| NMSE | 1.12889937 |
| MAE | 1386.360635 |
| Min Abs Error | 1.045980519 |
| Max Abs Error | 6386.386111 |
| r | 0.498748255 |

Test 34: XBLSM HISTORICAL WITH CHANGE, WITH WAP (from 2004-08-19 to 2009-12-31 for séance 1 and 2 with 8 Stocks)

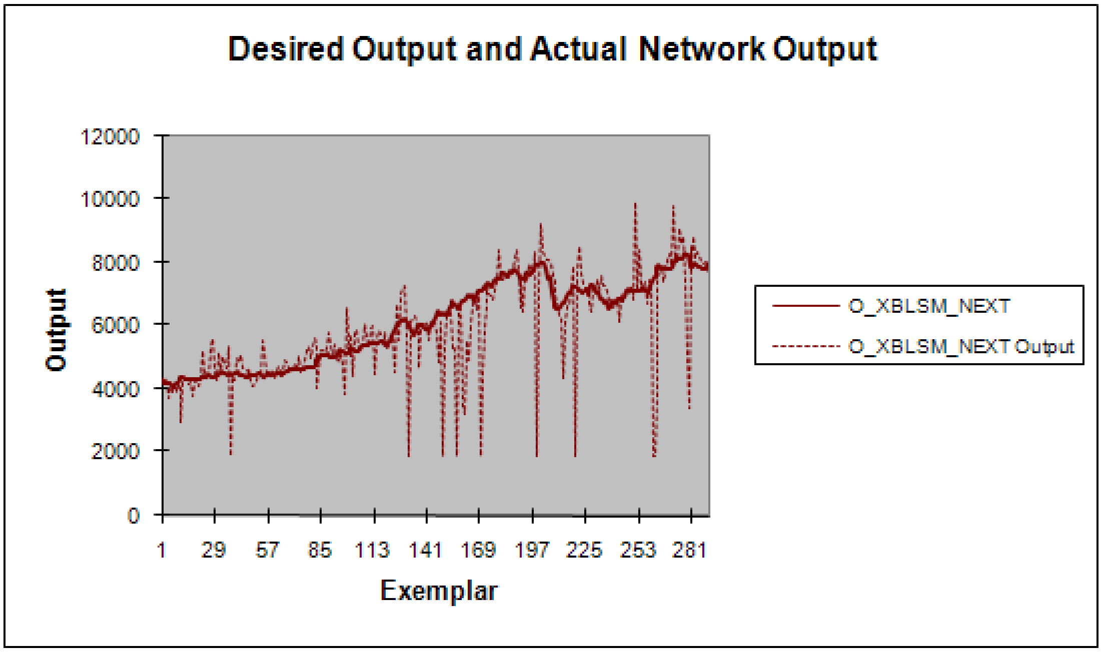


Figure 44: XBLSM séance 1,2 forecast with change with WAP Step 2

| Performance | O_XBLSM_NEXT |
|---|---|
| MSE | 1349486.651 |
| NMSE | 0.806474825 |
| MAE | 591.7536187 |
| Min Abs Error | 1.539728547 |
| Max Abs Error | 6054.232222 |
| r | 0.698439794 |

Test 35: XBANK HISTORICAL WITH CHANGE, WITH WAP (from 1997-01-02 to 2009-12-31 for séance 1 and 2 with 10 Stocks)

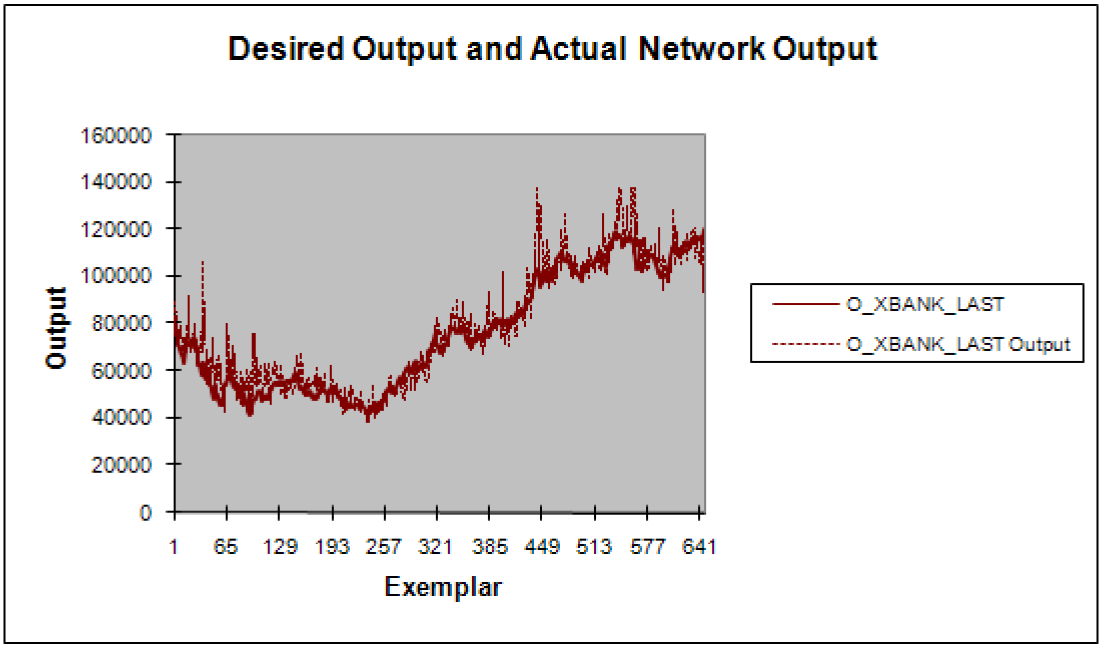


Figure 45: XBANK séance 1,2 forecast with change with WAP Step 1

| *Performance* | *O_XBANK_LAST* |
|---|---|
| MSE | 55715319.44 |
| NMSE | 0.091137856 |
| MAE | 5126.455754 |
| Min Abs Error | 26.04040994 |
| Max Abs Error | 42656.38678 |
| r | 0.962176604 |

Test 36: XBANK HISTORICAL WITH CHANGE, WITH WAP (from 1997-04-10 to 2009-12-31 for séance 1 and 2 with 11 Stocks)

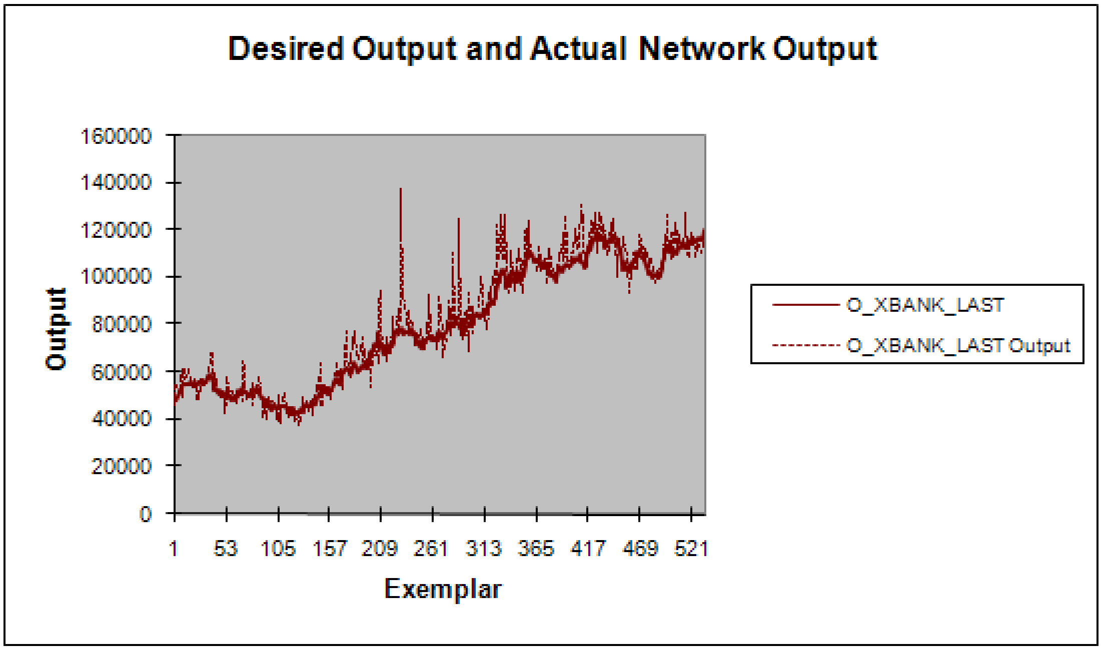


Figure 46: XBANK séance 1,2 forecast with change with WAP Step 2

| Performance | O_XBANK_LAST |
|---|---|
| MSE | 50499738.38 |
| NMSE | 0.080466728 |
| MAE | 4749.09889 |
| Min Abs Error | 1.406126367 |
| Max Abs Error | 59977.61056 |
| r | 0.968504602 |

Test 37: XBANK HISTORICAL WITH CHANGE, WITH WAP (from 2000-02-28 to 2009-12-31 for séance 1 and 2 with 12 Stocks)

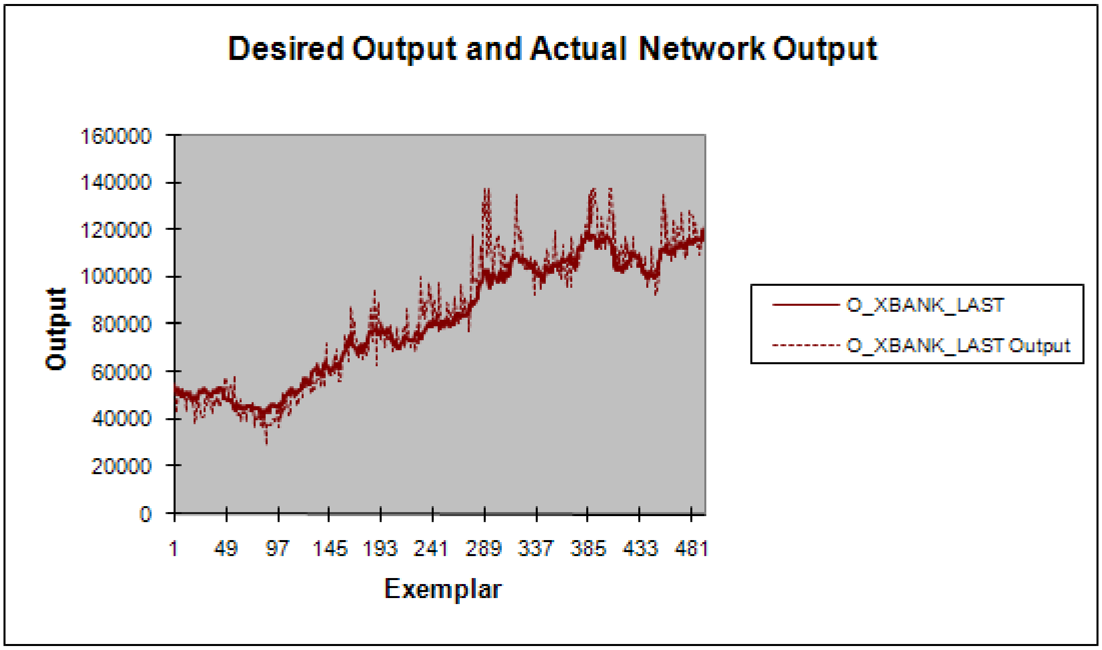


Figure 47: XBANK séance 1,2 forecast with change with WAP Step 3

| *Performance* | *O_XBANK_LAST* |
|---|---|
| MSE | 56974739.5 |
| NMSE | 0.091701716 |
| MAE | 5329.989439 |
| Min Abs Error | 11.7357027 |
| Max Abs Error | 37796.7529 |
| r | 0.970183993 |

Test 38: XBANK HISTORICAL WITH CHANGE, WITH WAP (from 2004-10-01 to 2009-12-31 for séance 1 and 2 with 13 Stocks)

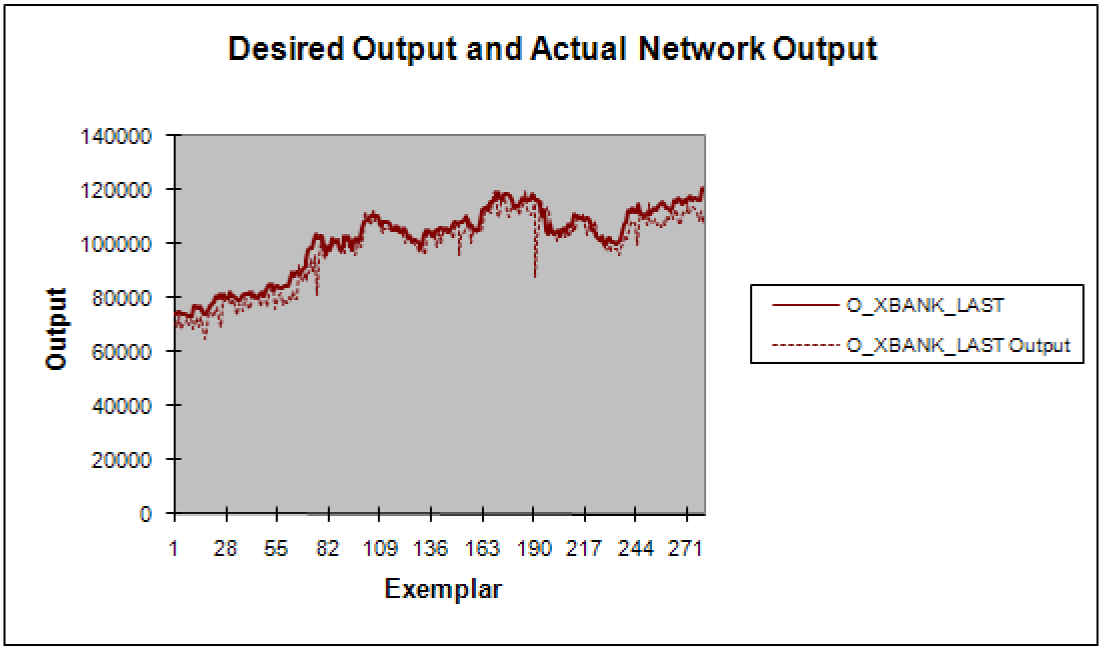


Figure 48: XBANK séance 1,2 forecast with change with WAP Step 4

| *Performance* | *O_XBANK_LAST* |
|---|---|
| MSE | 24452229.69 |
| NMSE | 0.142570606 |
| MAE | 3686.396791 |
| Min Abs Error | 96.85116217 |
| Max Abs Error | 29525.33495 |
| r | 0.960270312 |

Test 39: XBANK HISTORICAL WITH CHANGE, WITH WAP (from 2006-05-12 to 2009-12-31 for séance 1 and 2 with 16 Stocks)

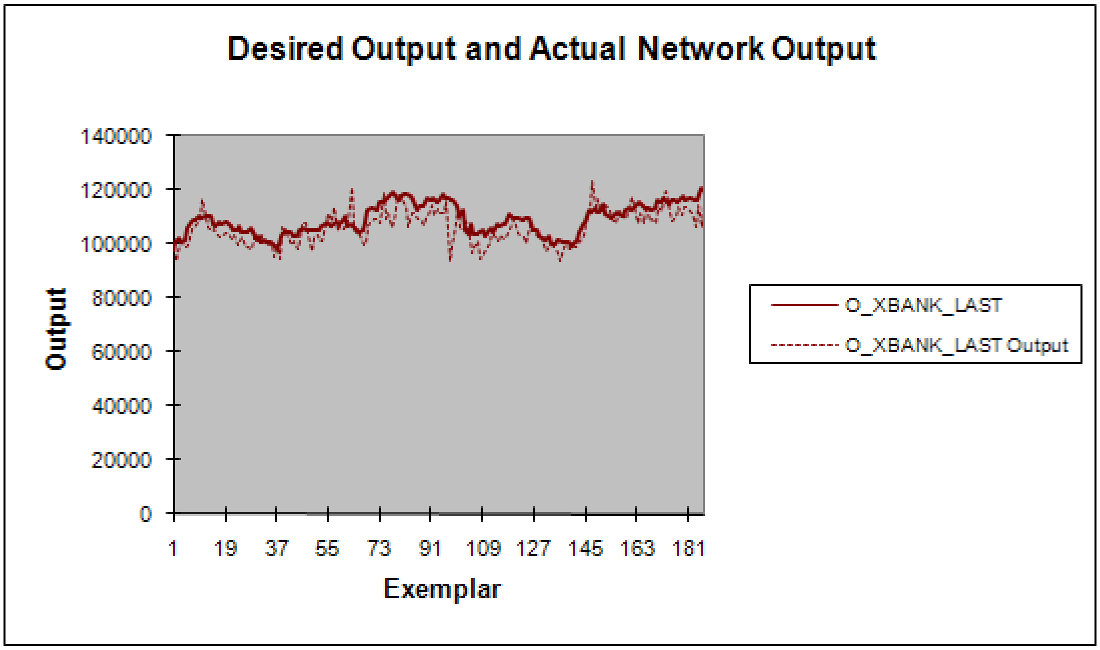


Figure 49: XBANK séance 1,2 forecast with change with WAP Step 5

| Performance | O_XBANK_LAST |
| --- | --- |
| MSE | 26787995.65 |
| NMSE | 0.895682661 |
| MAE | 4010.141905 |
| Min Abs Error | 23.71360607 |
| Max Abs Error | 23441.76871 |
| r | 0.739850237 |

Test 40: XBANK HISTORICAL WITH CHANGE, WITH WAP (from 2007-06-29 to 2009-12-31 for séance 1 and 2 with 18 Stocks)

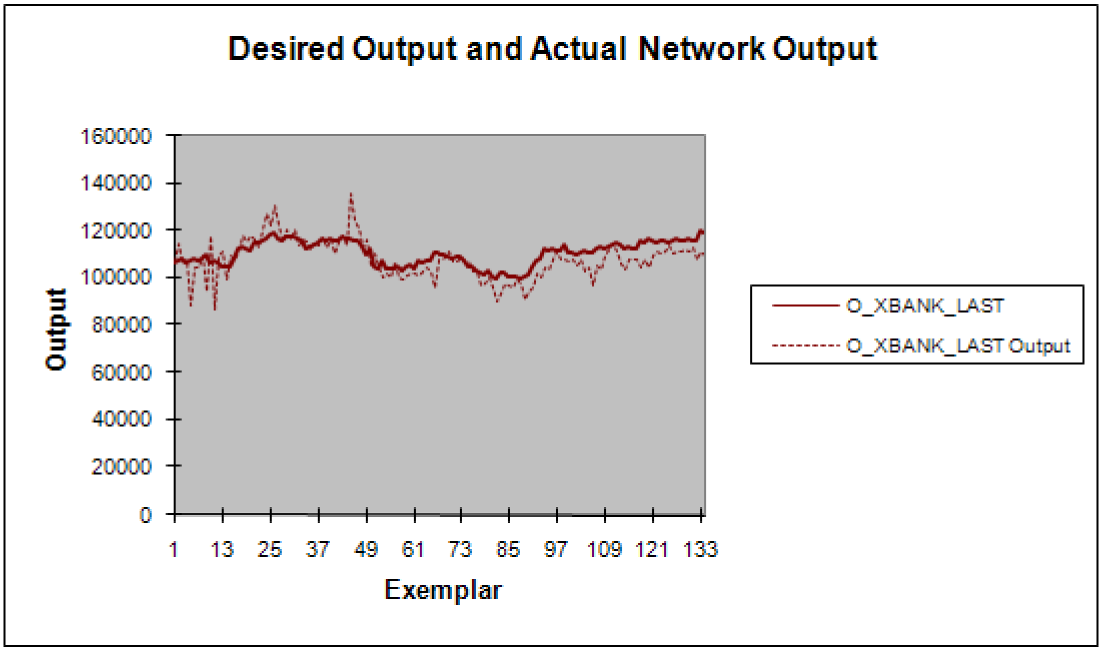


Figure 50: XBANK séance 1,2 forecast with change with WAP Step 6

| Performance | O_XBANK_LAST |
|---|---|
| MSE | 40461042.34 |
| NMSE | 1.438382922 |
| MAE | 5019.253435 |
| Min Abs Error | 19.01430305 |
| Max Abs Error | 20552.03235 |
| r | 0.732608188 |

STOCK BASED TESTS: In stock based tests, all the stocks which constitute the index are taken into account. As a result, training and testing time intervals are become shorter but none of the stocks are disregarded in computations.

Test 41: XTRZM STOCK BASED WITH CHANGE, WITH WAP (from 1997-01-02 to 2000-08-09 for séance 1 and 2 with 2 Stocks)

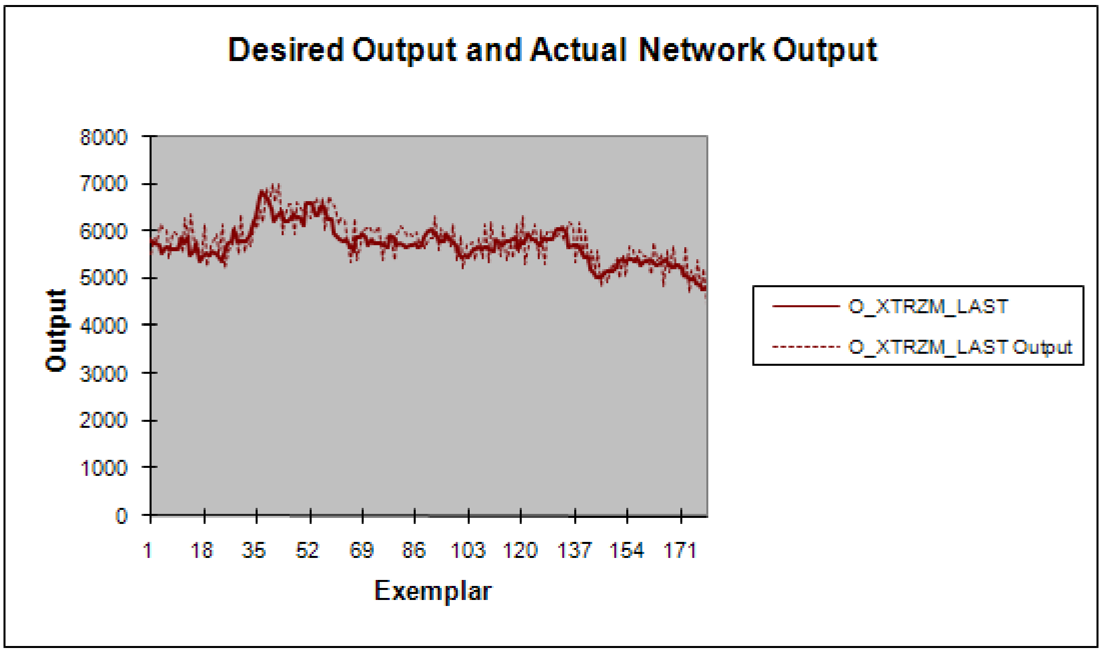


Figure 51: XTRZM Stock based forecast for Séance 1,2 Step 1

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 104577.5543 |
| NMSE | 0.674094728 |
| MAE | 273.381602 |
| Min Abs Error | 3.333683795 |
| Max Abs Error | 891.9496663 |
| r | 0.748487953 |

Test 42: XTRZM STOCK BASED WITH CHANGE, WITH WAP (from 2000-08-31 to 2008-12-31 for séance 1 and 2 with 4 Stocks)

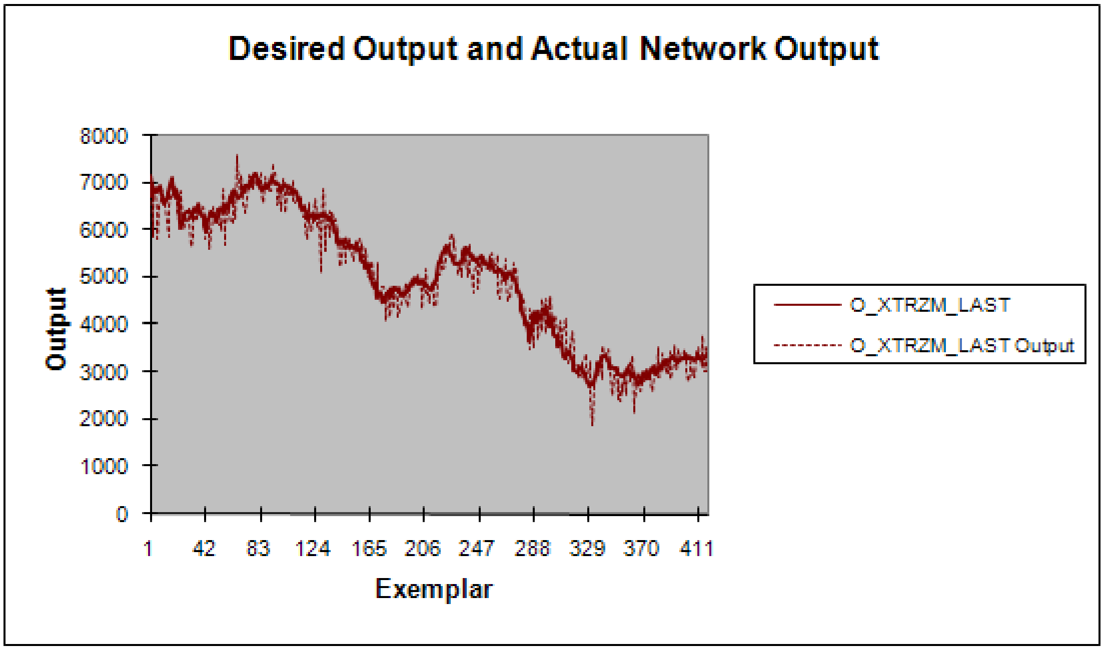


Figure 52: XTRZM Stock based forecast for Séance 1,2 Step 2

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 94916.24605 |
| NMSE | 0.04864162 |
| MAE | 235.9498447 |
| Min Abs Error | 0.226395159 |
| Max Abs Error | 1209.052756 |
| r | 0.976680479 |

Test 43: XTRZM STOCK BASED WITH CHANGE, WITH WAP (from 2009-01-02 to 2009-12-31 for séance 1 and 2 with 5 Stocks)

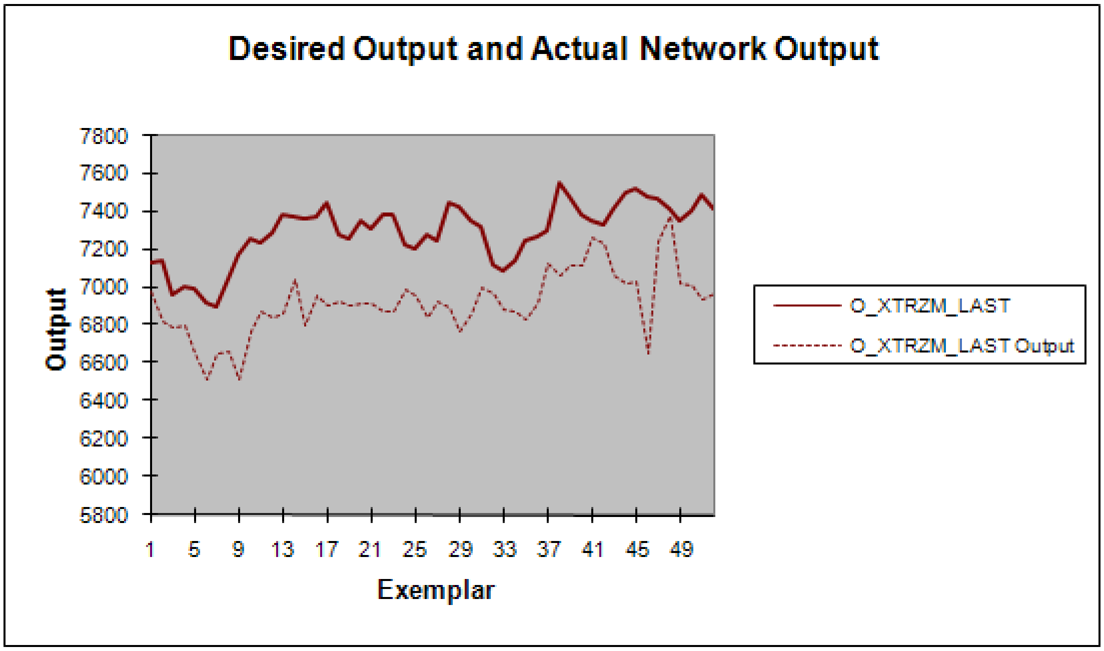


Figure 53: XTRZM Stock based forecast for Séance 1,2 Step 3

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 166156.8752 |
| NMSE | 6.352283529 |
| MAE | 375.6182551 |
| Min Abs Error | 35.69318639 |
| Max Abs Error | 835.7629319 |
| r | 0.550951019 |

Test 44: XTRZM STOCK BASED WITH CHANGE, WITHOUT WAP (from 2000-01-02 to 2009-12-31 for séance 1 and 2 with 2 Stocks)

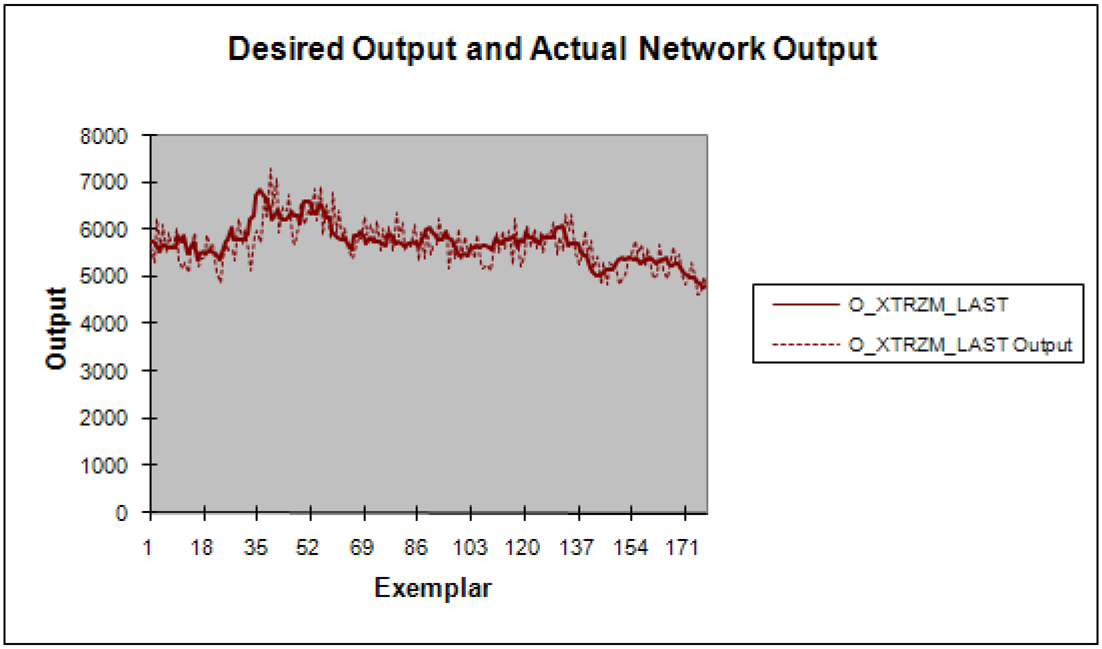


Figure 54: XTRZM Stock based forecast for Séance 1,2 Step 1

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 127270.8717 |
| NMSE | 0.816139185 |
| MAE | 290.3560391 |
| Min Abs Error | 3.043468921 |
| Max Abs Error | 1087.222888 |
| r | 0.684083593 |

Test 45: XTRZM STOCK BASED WITH CHANGE, WITHOUT WAP (from 2000-08-31 to 2008-12-31 for séance 1 and 2 with 4 Stocks)

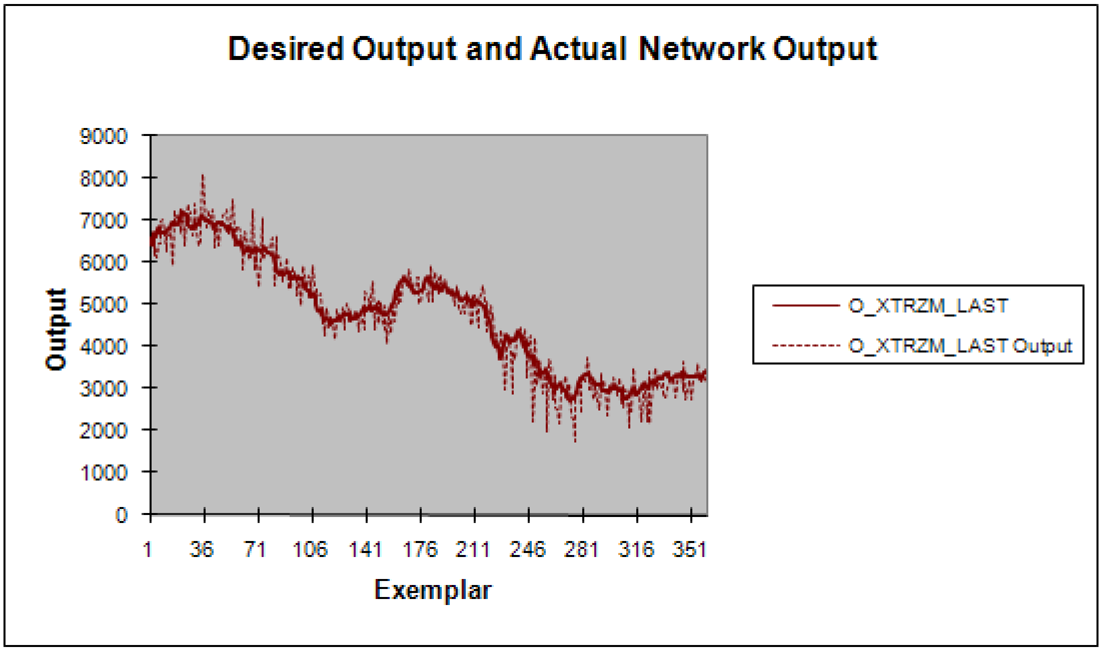


Figure 55: XTRZM Stock based forecast for Séance 1,2 Step 2

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 135556.8471 |
| NMSE | 0.073467321 |
| MAE | 280.6240256 |
| Min Abs Error | 1.27578769 |
| Max Abs Error | 1560.263333 |
| r | 0.969260338 |

Test 46: XTRZM STOCK BASED WITH CHANGE, WITHOUT WAP (from 2009-01-02 to 2009-12-31 for séance 1 and 2 with 5 Stocks)

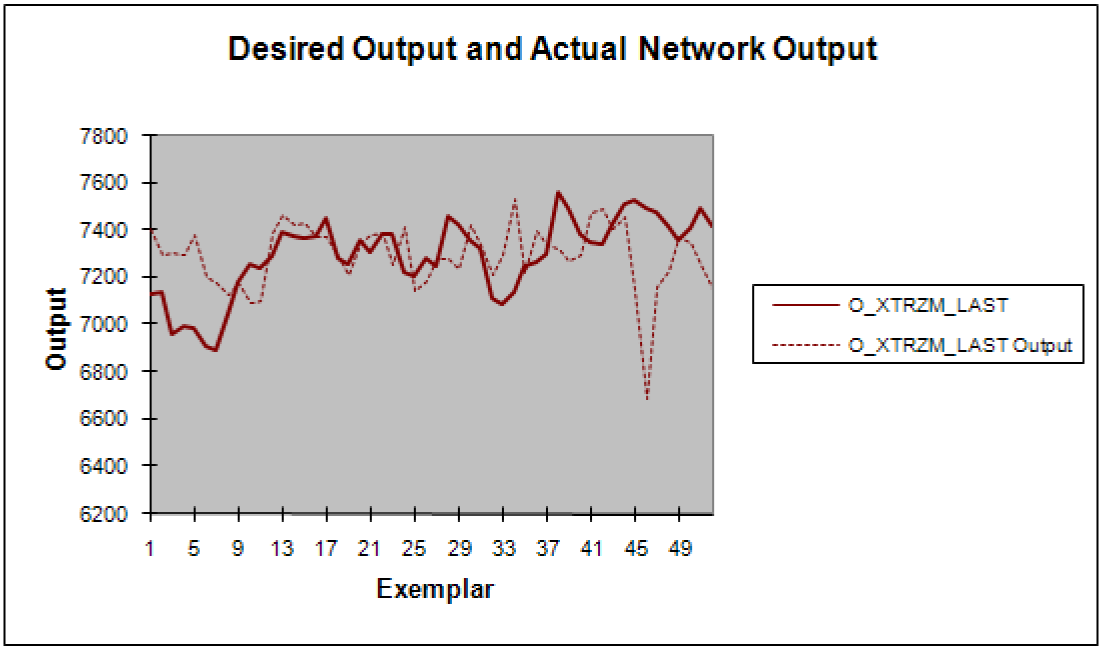


Figure 56: XTRZM Stock based forecast for Séance 1,2 Step 3

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 43677.81255 |
| NMSE | 1.669830688 |
| MAE | 152.1537338 |
| Min Abs Error | 1.021411728 |
| Max Abs Error | 800.034842 |
| r | 0.028145195 |

Test 47: XTRZM STOCK BASED WITHOUT CHANGE, WITHOUT WAP (from 2000-01-02 to 2009-12-31 for séance 1 and 2 with 2 Stocks)

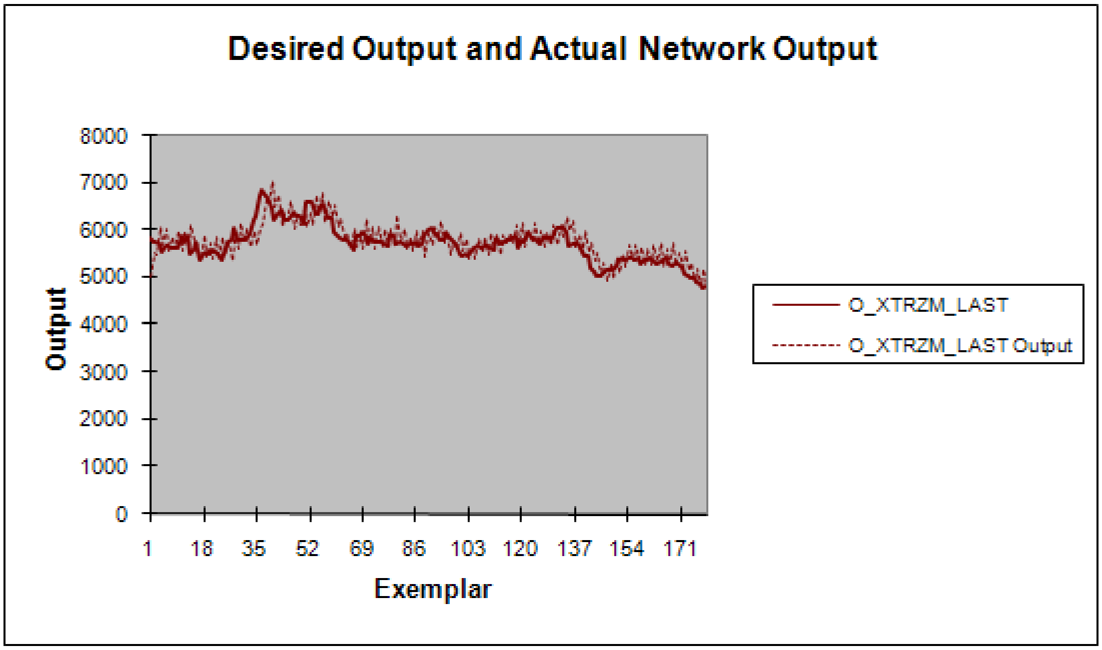


Figure 57: XTRZM Stock based forecast for Séance 1,2 Step 1

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 80161.64818 |
| NMSE | 0.516712643 |
| MAE | 226.2254854 |
| Min Abs Error | 2.016728396 |
| Max Abs Error | 825.1593239 |
| r | 0.754762444 |

Test 48: XTRZM STOCK BASED WITHOUT CHANGE, WITHOUT WAP (from 2000-08-31 to 2008-12-31 for séance 1 and 2 with 4 Stocks)

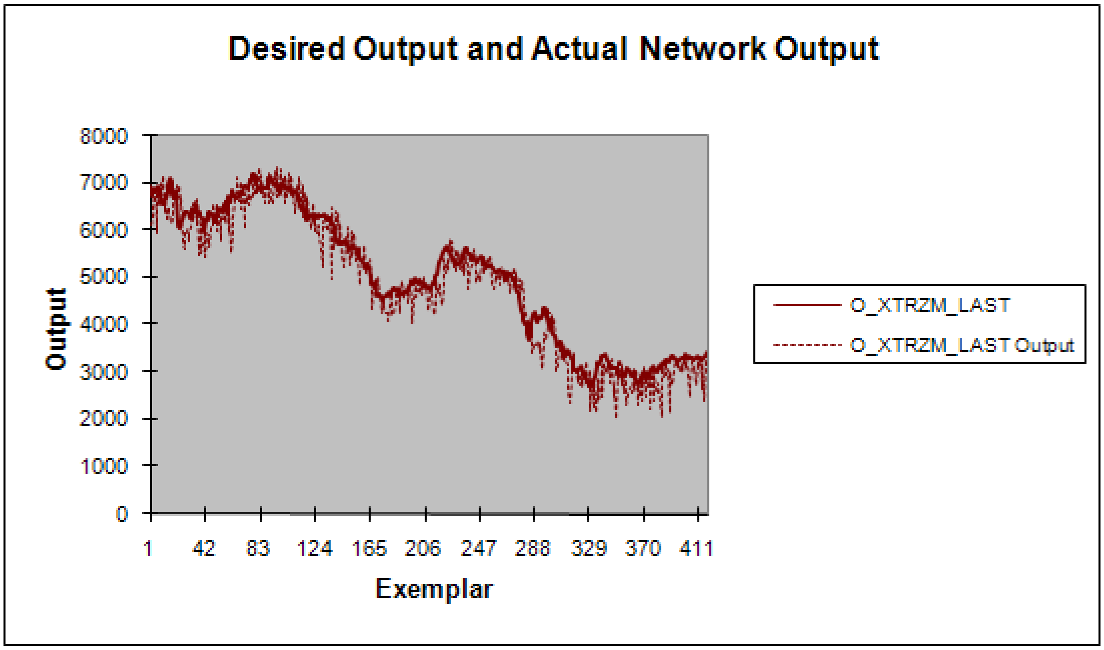


Figure 58: XTRZM Stock based forecast for Séance 1,2 Step 2

| *Performance* | *O_XTRZM_LAST* |
|---|---|
| MSE | 157762.5594 |
| NMSE | 0.081105907 |
| MAE | 313.1250834 |
| Min Abs Error | 0.410217145 |
| Max Abs Error | 1275.847064 |
| r | 0.971578273 |

Test 49: XTRZM STOCK BASED WITHOUT CHANGE, WITHOUT WAP (from 2009-01-02 to 2009-12-31 for séance 1 and 2 with 5 Stocks)

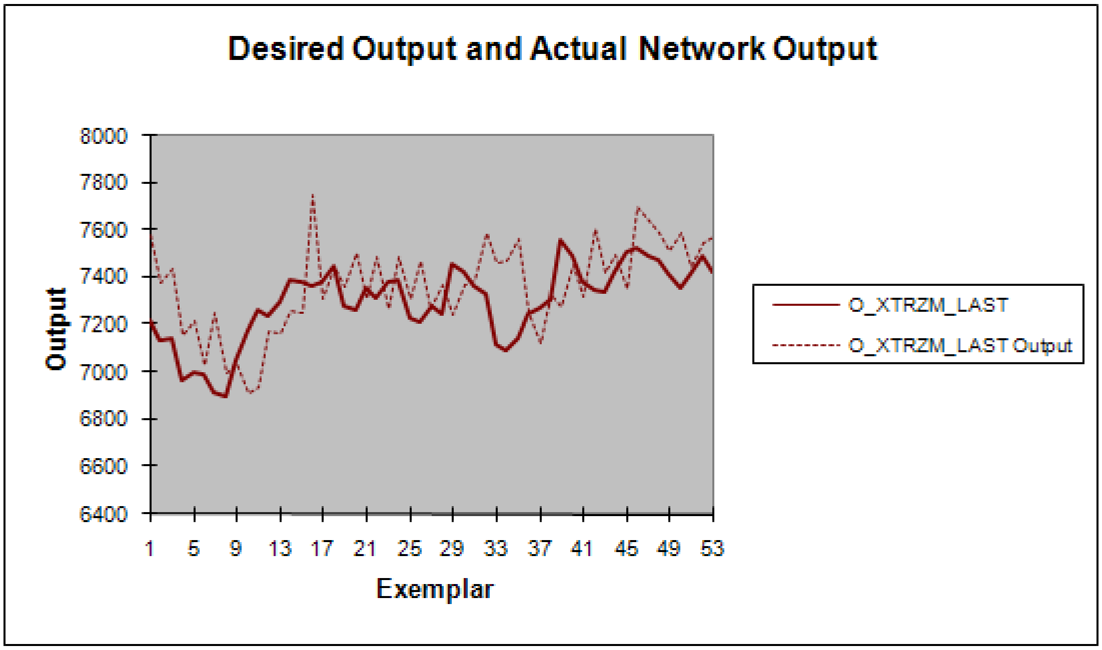


Figure 59: XTRZM Stock based forecast for Séance 1,2 Step 3

| Performance | O_XTRZM_LAST |
|---|---|
| MSE | 37654.90426 |
| NMSE | 1.460874125 |
| MAE | 157.4378517 |
| Min Abs Error | 1.819036677 |
| Max Abs Error | 416.051969 |
| r | 0.478990697 |

Test 50: XKMY STOCK BASED WITH CHANGE, WITH WAP (from 1997-01-02 to 1999-11-03 for séance 1 and 2 with 16 Stocks)

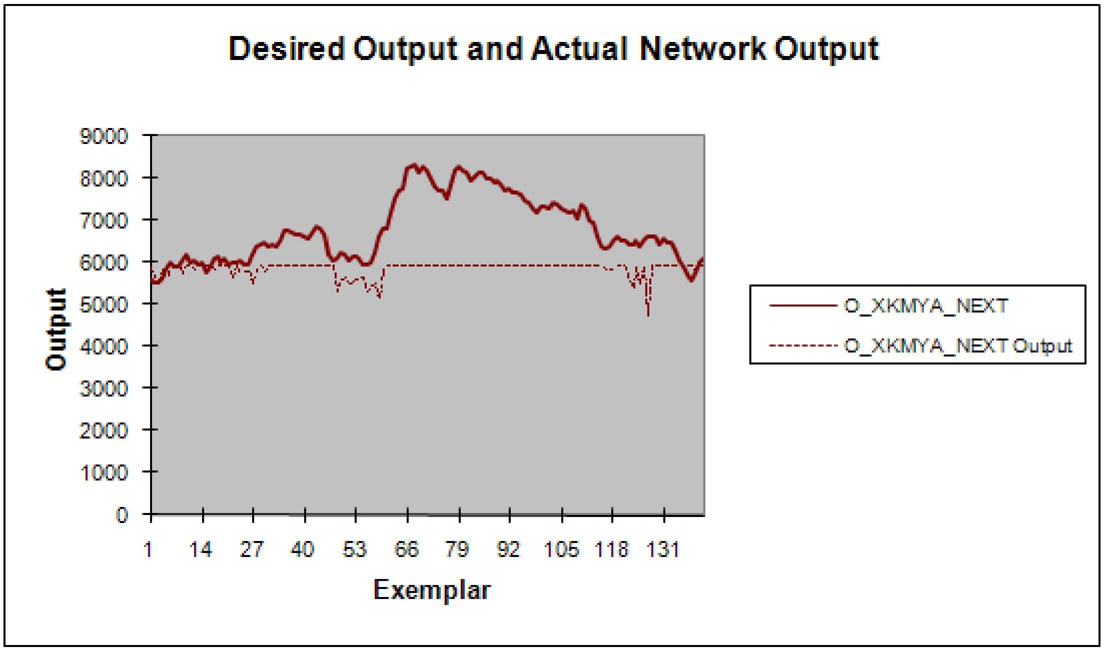


Figure 60: XKMY Stock based forecast for Séance 1,2 Step 1

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 1439994.372 |
| NMSE | 2.386916794 |
| MAE | 965.0783339 |
| Min Abs Error | 0.645721519 |
| Max Abs Error | 2394.628333 |
| r | 0.341705721 |

Test 51: XKMY STOCK BASED WITH CHANGE, WITH WAP (from 1999-11-03 to 2000-12-22 for séance 1 and 2 with 17 Stocks)

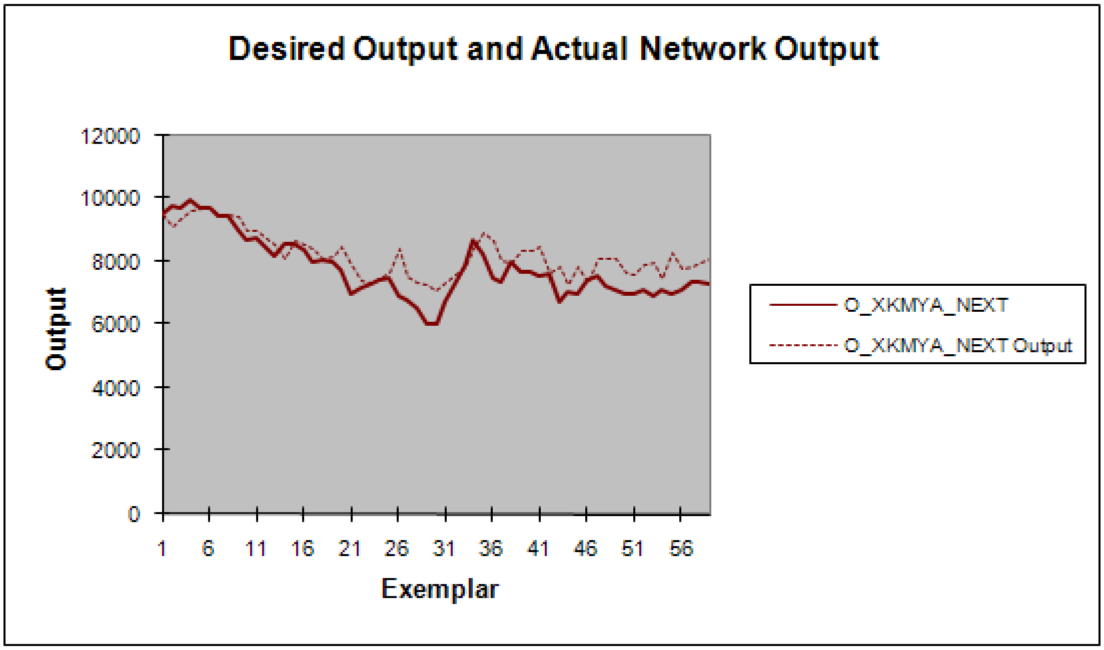


Figure 61: XKMY Stock based forecast for Séance 1,2 Step 2

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 405065.2177 |
| NMSE | 0.435122073 |
| MAE | 509.9861433 |
| Min Abs Error | 6.717276759 |
| Max Abs Error | 1496.243055 |
| r | 0.894277749 |

Test 52: XKMY STOCK BASED WITH CHANGE, WITH WAP (from 2001-01-02 to 2001-12-28 for séance 1 and 2 with 19 Stocks)

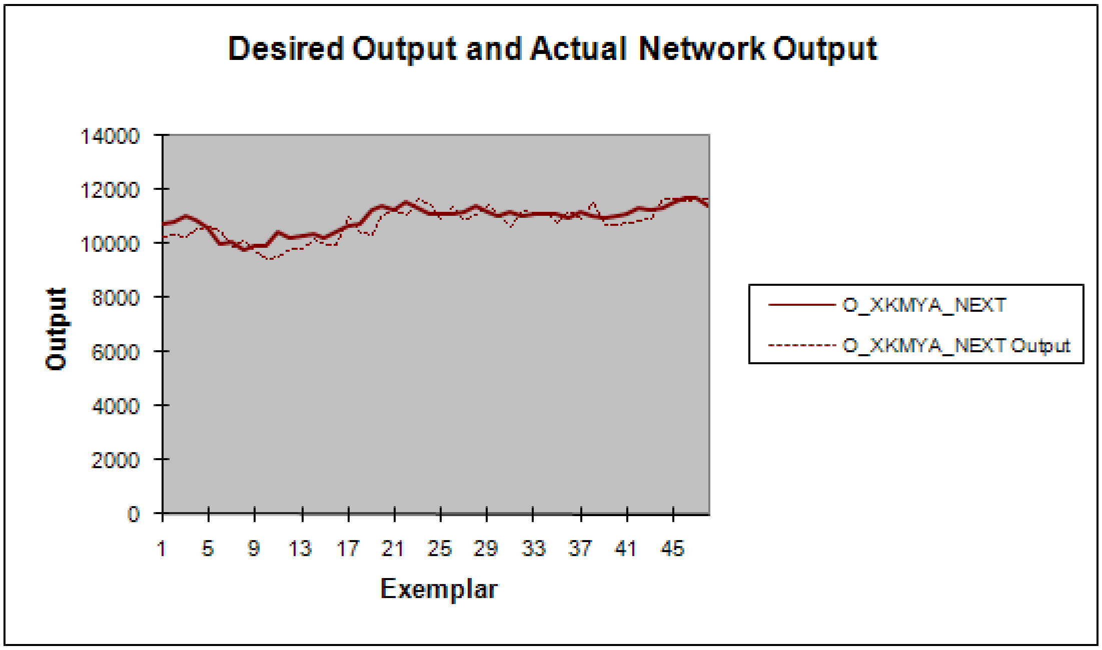


Figure 62: XKMY Stock based forecast for Séance 1,2 Step 3

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 170722.1599 |
| NMSE | 0.718727272 |
| MAE | 348.6062724 |
| Min Abs Error | 37.61055556 |
| Max Abs Error | 1016.227908 |
| r | 0.821923343 |

Test 53: XKMY STOCK BASED WITH CHANGE, WITH WAP (from 2003-01-02 to 2009-12-31 for séance 1 and 2 with 20 Stocks)

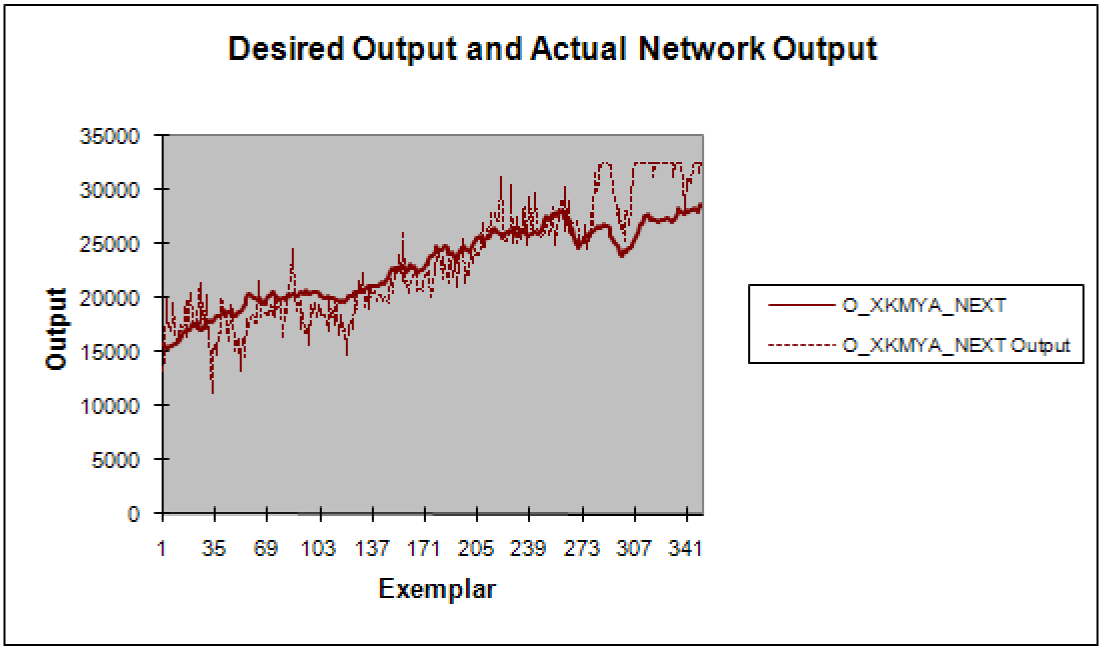


Figure 63: XKMY Stock based forecast for Séance 1,2 Step 4

| Performance | O_XKMYA_NEXT |
|---|---|
| MSE | 7565819.218 |
| NMSE | 0.595867709 |
| MAE | 2144.520311 |
| Min Abs Error | 3.021613791 |
| Max Abs Error | 7185.39 |
| r | 0.893212314 |

Test 54: XGIDA STOCK BASED WITH CHANGE, WITH WAP (from 1997-01-02 to 1997-08-18 for séance 1 and 2 with 11 Stocks)

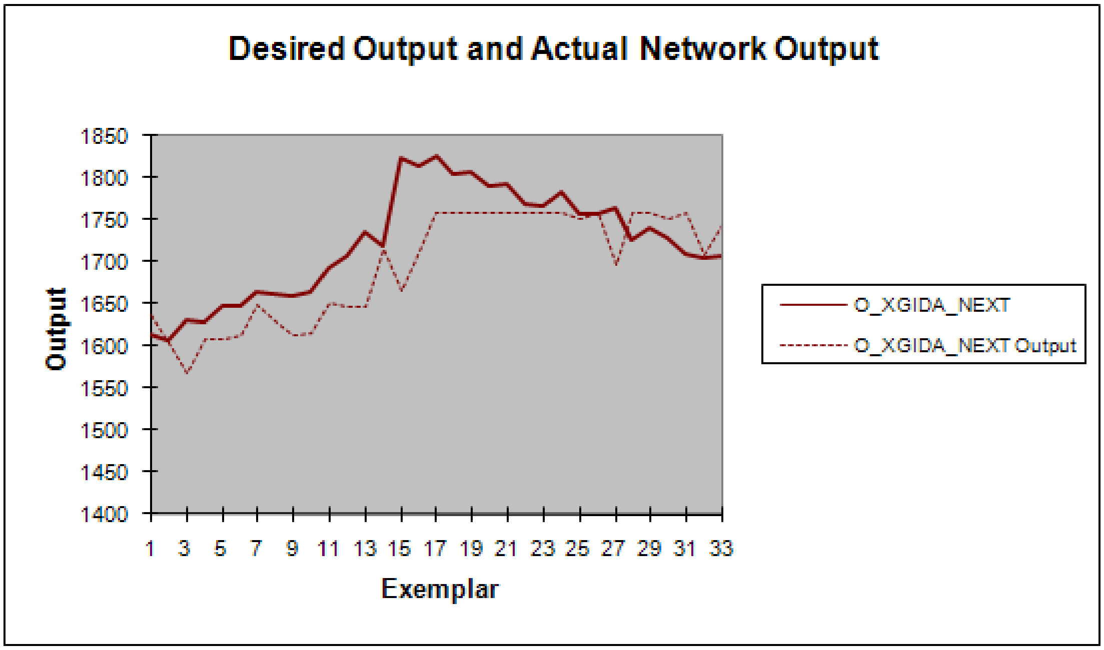


Figure 64: XGIDA Stock based forecast for Séance 1,2 Step 1

| Performance | O_XGIDA_NEXT |
|---|---|
| MSE | 2578.434638 |
| NMSE | 0.620946176 |
| MAE | 39.16648931 |
| Min Abs Error | 0.417222222 |
| Max Abs Error | 157.5059407 |
| r | 0.784067665 |

Test 55: XGIDA STOCK BASED WITH CHANGE, WITH WAP (from 2000-08-11 to 2004-02-20 for séance 1 and 2 with 18 Stocks)

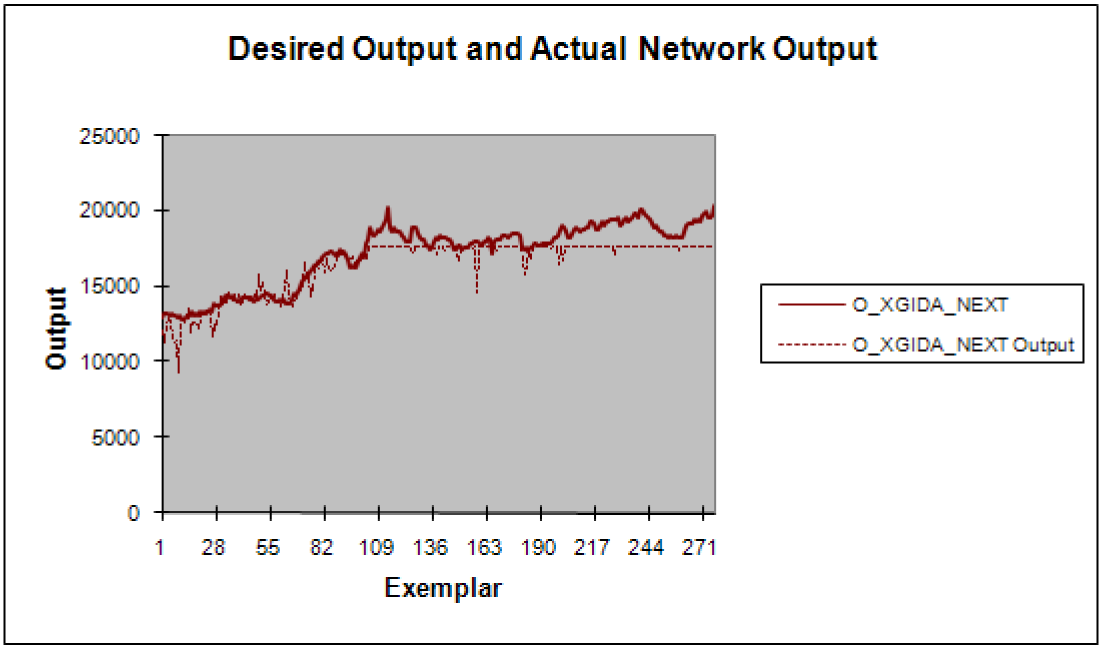


Figure 65: XGIDA Stock based forecast for Séance 1,2 Step 2

| Performance | O_XGIDA_NEXT |
|---|---|
| MSE | 1264772.927 |
| NMSE | 0.279272239 |
| MAE | 885.4220795 |
| Min Abs Error | 1.523445399 |
| Max Abs Error | 3720.031501 |
| r | 0.928115564 |

Test 56: XGIDA STOCK BASED WITH CHANGE, WITH WAP (from 2004-02-23 to 2005-05-11 for séance 1 and with 19 Stocks)

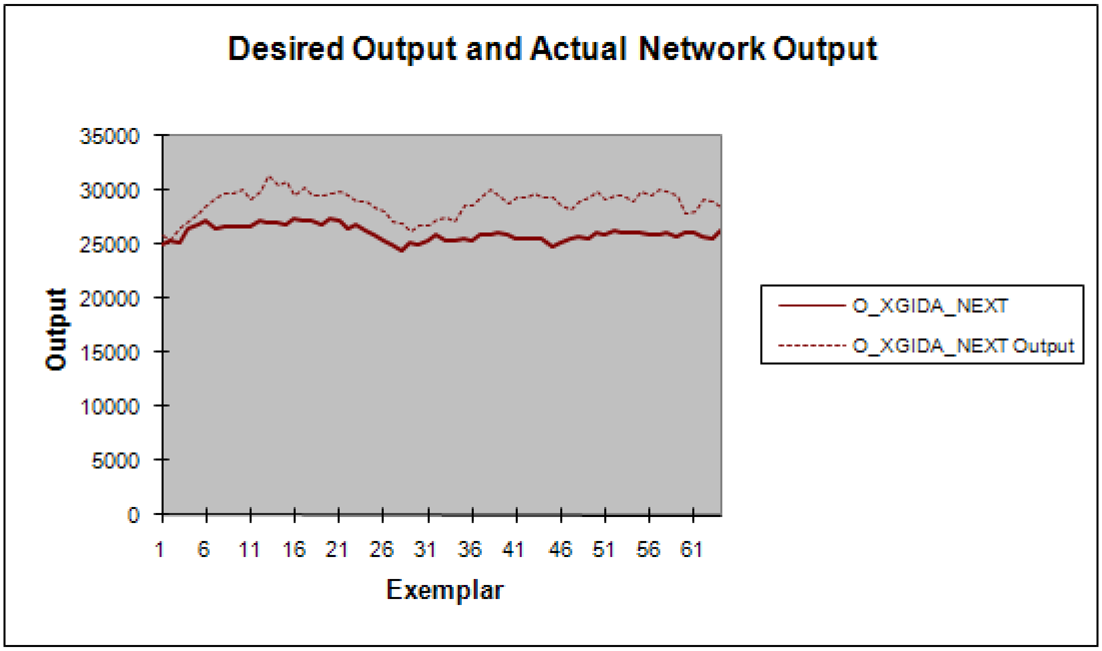


Figure 66: XGIDA Stock based forecast for Séance 1,2 Step 3

| Performance | O_XGIDA_NEXT |
|---|---|
| MSE | 9382240.998 |
| NMSE | 18.92537979 |
| MAE | 2901.125987 |
| Min Abs Error | 190.6144333 |
| Max Abs Error | 4659.702112 |
| r | 0.606238244 |

Test 57: XGIDA STOCK BASED WITH CHANGE, WITH WAP (from 2006-05-12 to 2005-12-01 for séance 1 and 2 with 20 Stocks)

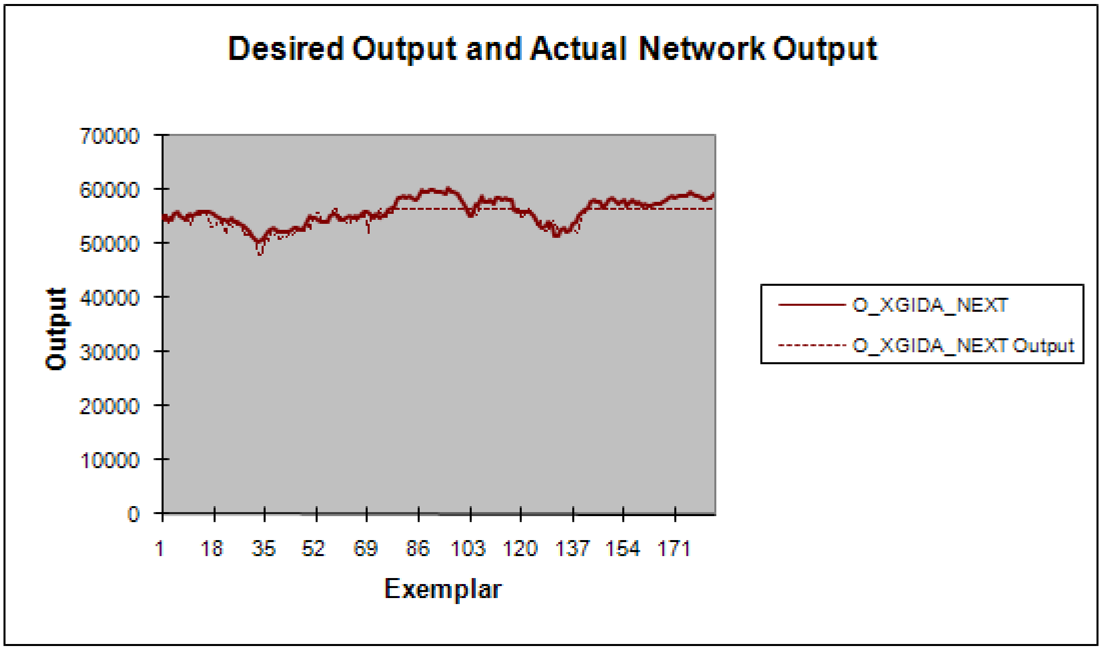


Figure 67: XGIDA Stock based forecast for Séance 1,2 Step 4

| Performance | O_XGIDA_NEXT |
|---|---|
| MSE | 2804955.343 |
| NMSE | 0.511765201 |
| MAE | 1361.740497 |
| Min Abs Error | 20.49111111 |
| Max Abs Error | 3984.591111 |
| r | 0.867340979 |

Test 58: XBLSM STOCK BASED WITH CHANGE, WITH WAP (from 2000-11-02 to 2004-06-18 for séance 1 and 2 with 6 Stocks)

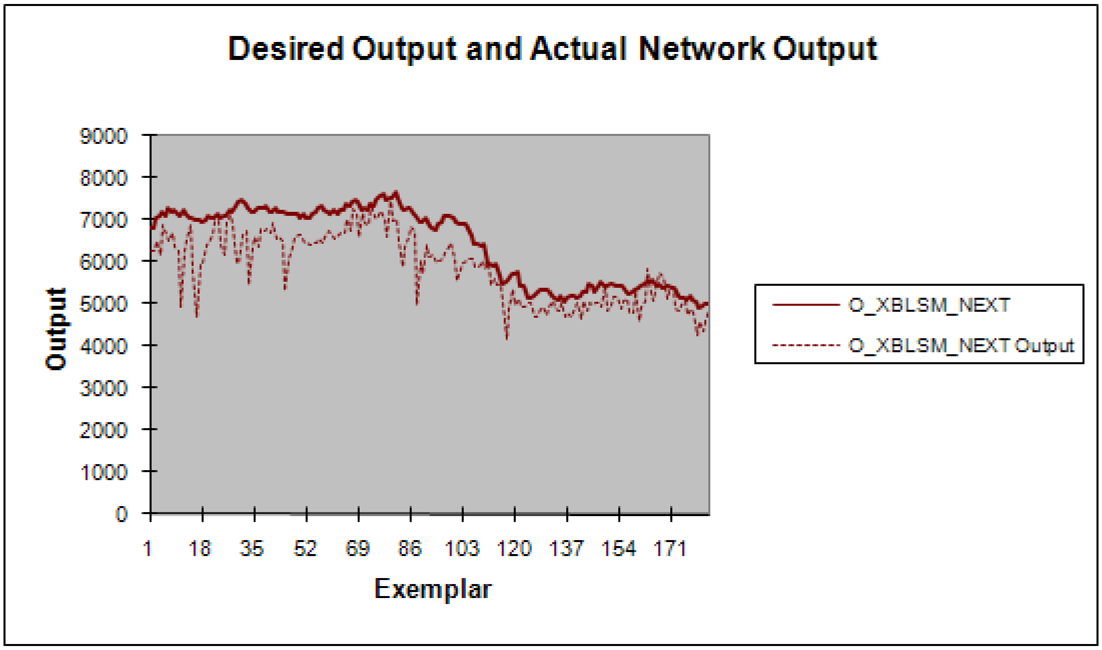


Figure 68: XBLSM Stock based forecast for Séance 1,2 Step 1

| Performance | O_XBLSM_NEXT |
|---|---|
| MSE | 498618.4202 |
| NMSE | 0.610093719 |
| MAE | 591.3947461 |
| Min Abs Error | 0.626428305 |
| Max Abs Error | 2342.700557 |
| r | 0.89546412 |

Test 59: XBLSM STOCK BASED WITH CHANGE, WITH WAP (from 2004-08-19 to 2005-09-12 for séance 1 and 2 with 8 Stocks)

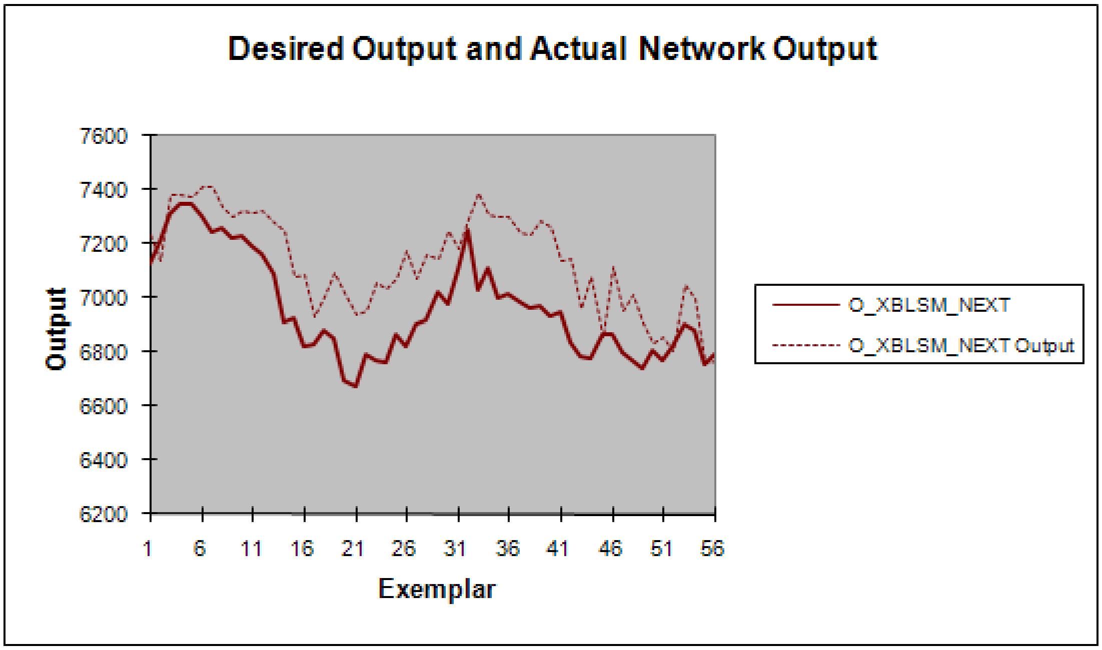


Figure 69: XBLSM Stock based forecast for Séance 1,2 Step 2

| Performance | O_XBLSM_NEXT |
|---|---|
| MSE | 40571.15726 |
| NMSE | 1.190039172 |
| MAE | 174.4019062 |
| Min Abs Error | 2.741086534 |
| Max Abs Error | 363.858323 |
| r | 0.820660817 |

Test 60: XBLSM STOCK BASED WITH CHANGE, WITH WAP (from 2006-10-20 to 2009-12-31 for séance 1 and 2 with 10 Stocks)

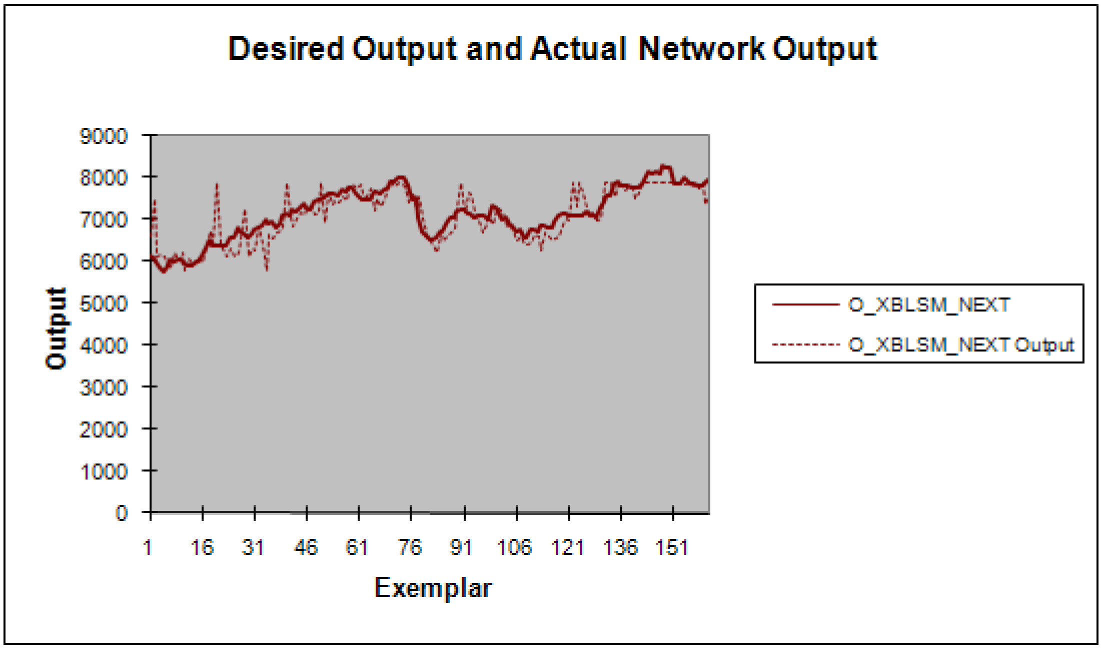


Figure 70: XBLSM Stock based forecast for Séance 1,2 Step 3

| Performance | O_XBLSM_NEXT |
|---|---|
| MSE | 114180.8362 |
| NMSE | 0.303722869 |
| MAE | 246.9925969 |
| Min Abs Error | 0.506666667 |
| Max Abs Error | 1476.106667 |
| r | 0.859450302 |

Test 61: XBANK STOCK BASED WITH CHANGE, WITH WAP (from 1997-01-02 to 1997-04-09 for séance 1 and 2 with 10 Stocks)

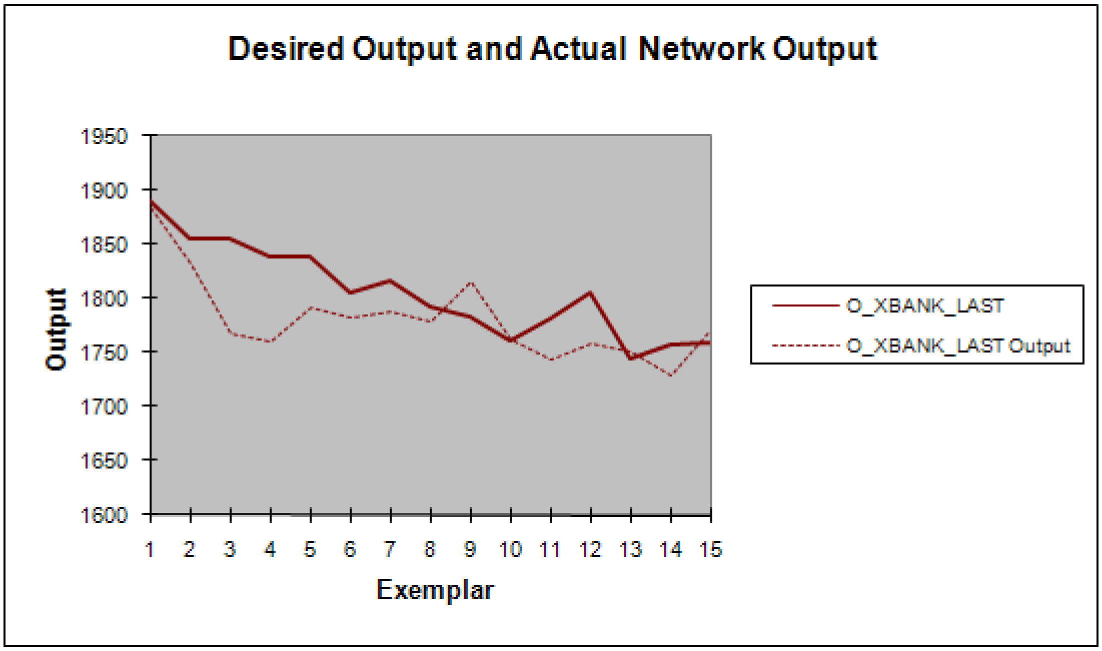


Figure 71: XBANK Stock based forecast for Séance 1,2 Step 1

| Performance | O_XBANK_LAST |
|---|---|
| MSE | 1640.57175 |
| NMSE | 0.926484174 |
| MAE | 32.17035027 |
| Min Abs Error | 0.978331345 |
| Max Abs Error | 89.96906015 |
| r | 0.687412231 |

Test 62: XBANK STOCK BASED WITH CHANGE, WITH WAP (from 2000-02-28 to 2004-09-30 for séance 1 and 2 with 12 Stocks)

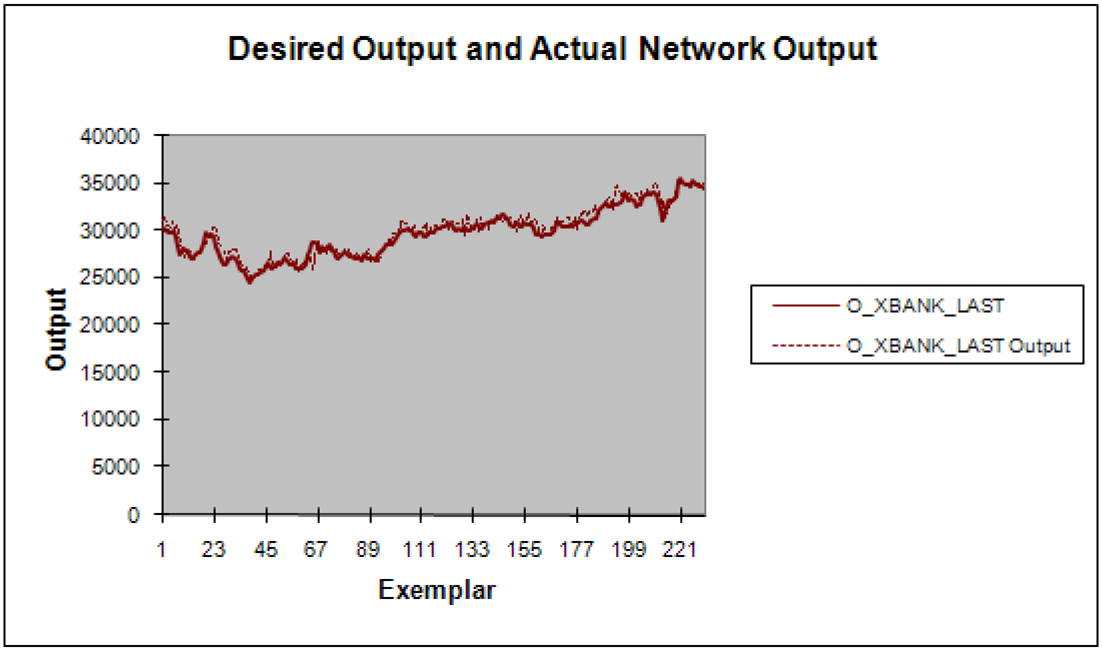


Figure 72: XBANK Stock based forecast for Séance 1,2 Step 2

| Performance | O_XBANK_LAST |
|---|---|
| MSE | 485313.6652 |
| NMSE | 0.075647371 |
| MAE | 545.6459879 |
| Min Abs Error | 6.381773121 |
| Max Abs Error | 2845.830648 |
| r | 0.970441317 |

Test 63: XBANK STOCK BASED WITH CHANGE, WITH WAP (from 2004-10-01 to 2005-11-17 for séance 1 and 2 with 13 Stocks)

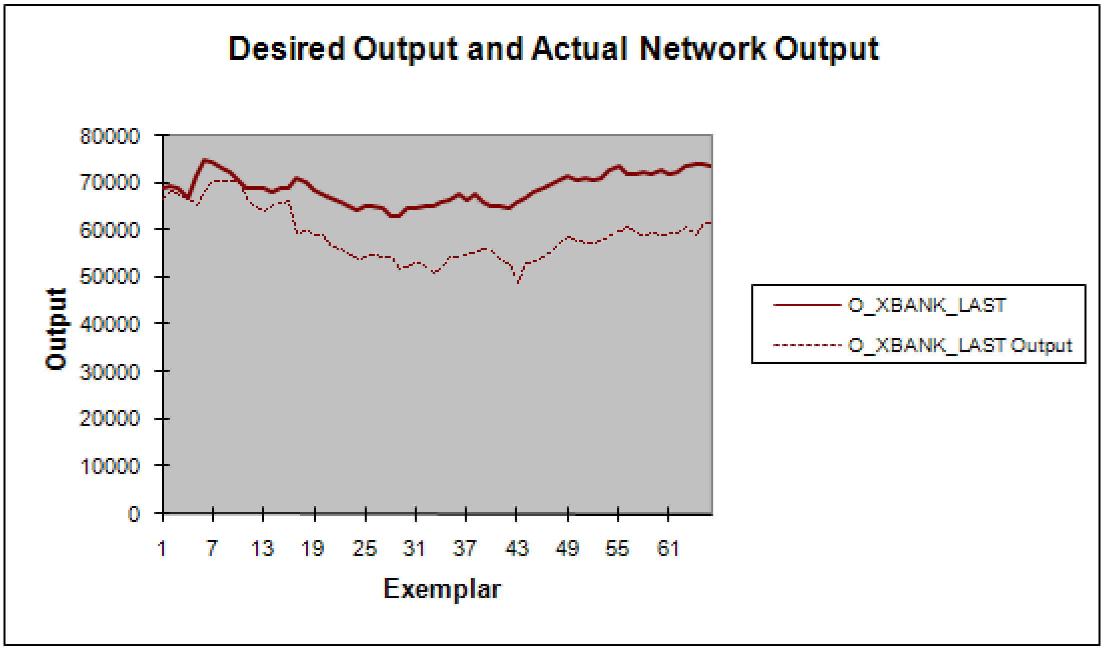


Figure 73: XBANK Stock based forecast for Séance 1,2 Step 3

| *Performance* | *O_XBANK_LAST* |
|---|---|
| MSE | 118890015.2 |
| NMSE | 11.39188518 |
| MAE | 9986.191705 |
| Min Abs Error | 186.7172312 |
| Max Abs Error | 17115.57527 |
| r | 0.611912062 |

Test 64: XBANK STOCK BASED WITH CHANGE, WITH WAP (from 2006-05-12 to 2007-05-09 for séance 1 and 2 with 16 Stocks)

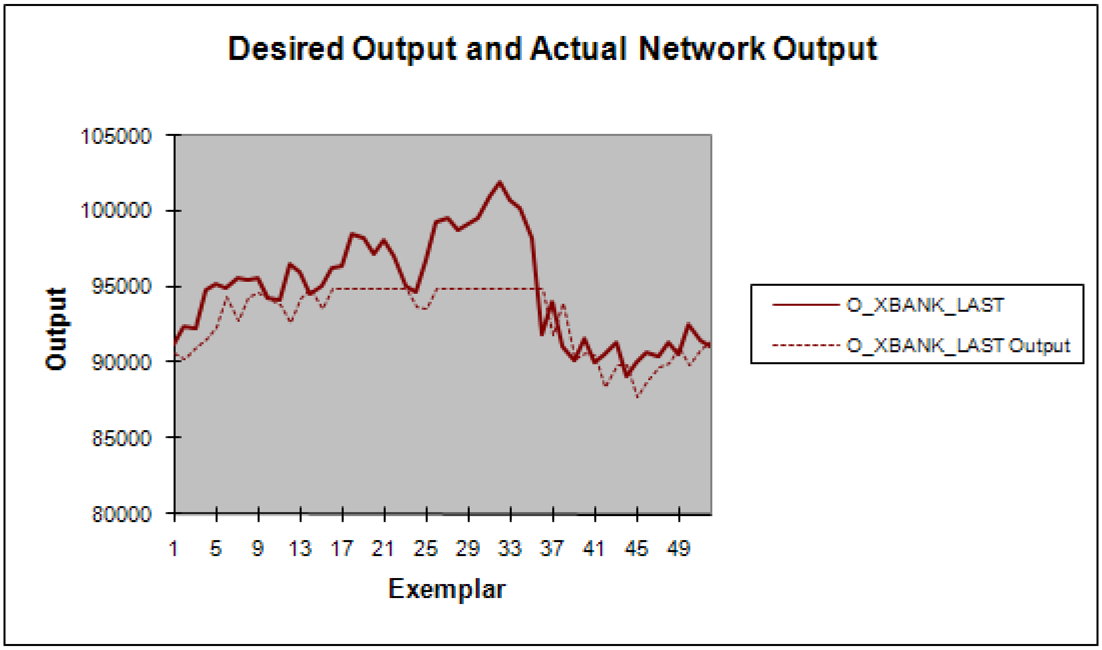


Figure 74: XBANK Stock based forecast for Séance 1,2 Step 4

| Performance | O_XBANK_LAST |
|---|---|
| MSE | 8419104.313 |
| NMSE | 0.709470579 |
| MAE | 2338.350797 |
| Min Abs Error | 93.47284448 |
| Max Abs Error | 7130.362222 |
| r | 0.818983785 |

Test 65: XBANK STOCK BASED WITH CHANGE, WITH WAP (from 2007-06-29 to 2009-12-31 for séance 1 and 2 with 18 Stocks)

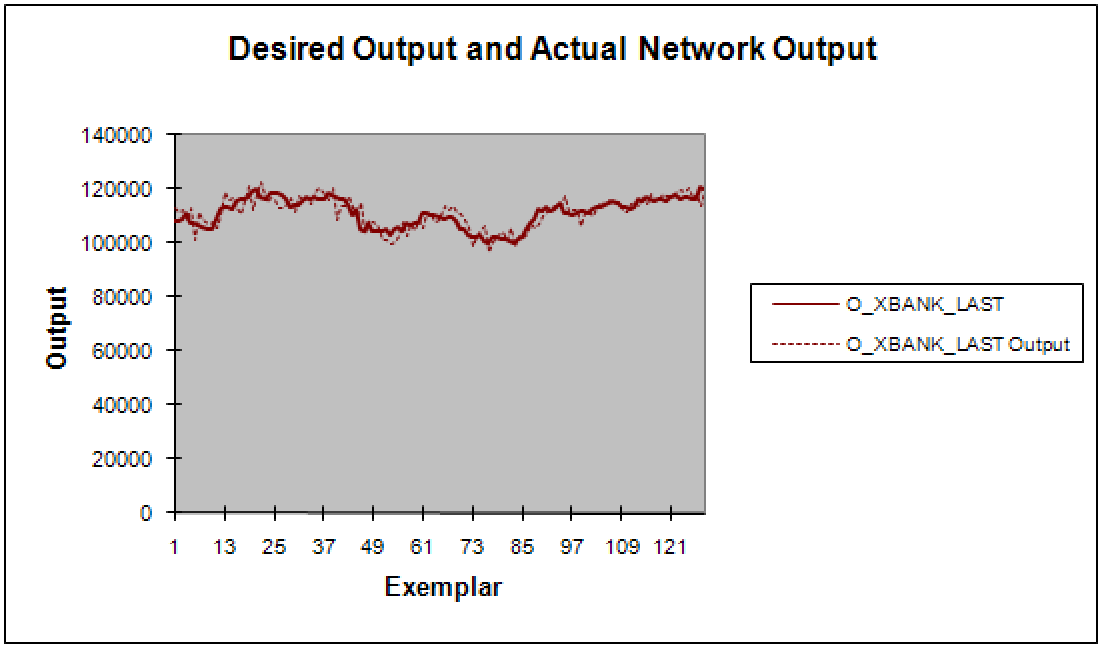


Figure 75: XBANK Stock based forecast for Séance 1,2 Step 5

| *Performance* | *O_XBANK_LAST* |
|---|---|
| MSE | 10308223.94 |
| NMSE | 0.358604266 |
| MAE | 2642.438977 |
| Min Abs Error | 43.47984214 |
| Max Abs Error | 9758.706221 |
| r | 0.834515166 |

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