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time-series prediction; data mining; neural network; modelling

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DATA MINING WORKSPACE AS AN OPTIMIZATION PREDICTION TECHNIQUE FOR SOLVING TRANSPORT PROBLEMS

Summary. This article addresses the study related to forecasting with an actual high-speed decision making under careful modelling of time series data. The study uses data-mining modelling for algorithmic optimization of transport goals. Our finding brings to the future adequate techniques for the fitting of a prediction model. This model is going to be used for analyses of the future transaction costs in the frontiers of the Czech Republic. Time series prediction methods for the performance of prediction models in the package of Statistics are Exponential, ARIMA and Neural Network approaches. The primary target for a predictive scenario in the data mining workspace is to provide modelling data faster and with more versatility than the other management techniques.

РЕШЕНИЕ ЗАДАЧИ ПРОГНОЗИРОВАНИЯ В ТРАНСПОРТНОЙ ОТРАСЛИ С ПОМОЩЬЮ МЕТОДОВ DATA MINING

Аннотация. В данной статье рассматривается задача прогнозирования временных рядов, которая заключается в построении модели для предсказания будущих событий. В исследовании используются методы интеллектуального анализа данных. Модель прогнозирования позволяет адекватно оценивать исследуемый процесс. Целью исследования является изучение динамики расходов при реализации экспортной продукции. Прогнозирование осуществляется с помощью ARIMA-модели, на основе метода экспоненциального сглаживания и по технологии логической нейронной сети. Построение базового и быстрого сценария прогнозирования является важным и ответственным этапом в научной деятельности.

1. INTRODUCTION

Predictive analysis and algorithms are essential for the most important issue of a well-functioning economic system for optimization problems in transportation system planning. Evaluation of future consequences can be approached from various methods and used to help improve transportation system planning. Prediction methods relate to assessment procedures and have been used in the field of manufacturing planning. From a prediction perspective, the effectiveness of leading forecasting approach becomes a powerful tool for changing of economic parameters, for example, future cost. Achieving accurate decision making in the manufacturing industry is not easy to come by. It requires smart and definitive methodologies or a thoughtful algorithm on how to get the suitable model from various prediction perspectives [28]. The paper introduces the current forecasting methodology for analysing the suitable procedure generating the probabilistic future outcomes. Forecasting methodology describes the characteristics and principles of Data mining modelling. The modelling tool in the data mining workspace is one from flexible instruments, which allows to reach the forecasting value of economic parameters and to increase future precision. We model future predictions with the improved technique process in the following manner: how to set up management tools to gain the best economic advantages. The major principle of every possible future scenario of a manufacturing area is to realize business planning with transparent economic value.

The style of paper is arranged in the following steps. Section one reviews the problem of best access within the business units. Next section reflects the study of the progressive approaches with an intelligent programming module. In our practical section, the steps of modelling included:

1. To set data for prediction;
2. To activate procedure based on the progressive methods;
3. To measure the statistical value of the prediction process;
4. To increase the prediction performance.

2. OBJECTIVE OF PAPER

The changes in the trends of export cost in which the small local business units transformed into the large supply chains can be observed in the Czech Republic. The major strategy of the manufacturing units is the optimization of cost management planning. The Industrial strategy can be improved with the development of the prediction model. It includes the investigation of historical data to test the behaviour management plan. For this purpose, it had to monitor economic business units. Jack V. Michaels and William P. Wood [13] describe inquiry of production cost thus: *"Once the structure of production cost distribution is clear, one realises that the outsources actually influence the reduction of average variable with their professional approach, optimisation, and the restructuring of work processes."* Obviously, the present costs in the frontier of the Czech Republic are influenced by knowledge of the past cost exports.

The objective of our paper is comparison of statistical models for prediction data and to find flexible prediction tool for future transaction costs (the authors do not consider the influence of different factors on the prediction but offer to verify the validity of the studied methods). The chief issue of this work is to compare the value of the experimental result by the offered methods towards special goals. Outputs of research are based on strengths of techniques and are improved by their setting. This practice makes future solutions in the transport planning more amenable to ever-changing conditions. It means that a variety of prediction scenarios reduces the complexity problems in two applications: strategy production and cost behaviour. The implementation of the developed mathematical model has resulted in solving the problem of optimization [9, 25]. Milenkovič, Bojovič, Švadlenka and Melichar [16] represent one of the most successful and most popular advanced control methods in the analysis of stochastic variables.

The authors will choose a suitable predictive model by analysing graphical outputs. Evaluation of the selected model will be based on forecasting error. The present work is aimed at solving actual scientific problems such as the development of modern attractive tools for transport studies. The authors provide predictions from data on direct trading costs connected with transport at the frontier of the Czech Republic (the CZK million, current prices). These data from January 2005 to December 2014 are used for the building of a prediction model for future transaction costs [36]. The authors in this issue use obtained data for the modelling feature of this study and for defining the measurements in the real environment.

3. DATA MINING METROLOGIES

Managers have the same hints of the development business situation. It is important to create a framework of the model with opportunities to use deep analyses. The data mining model is a representation of the real thing that reduces complexity and represents only the detailed needs of specific purposes. The data mining technique discovers noticeable platform for prediction tasks. Data mining consists of the set of modelling instruments needed to create a predictive model that is oriented on the experiment process. Successful implementation is based on understanding the all-out issues and demonstrates how all the elements relate together. The main advantage of data mining is an examination of every unit that might have an effect on the output. Data mining covers various techniques for determining which alternatives will be suitable for investigation. The final model reflects the best relationship in the data [11, 18, 23, 24, 26, 29, 30]. Steps of data mining include the next content of the modelling procedure:

1. Process definition. Identification of objective for analyses.
2. Selection of the data. It is based on the knowledge of the management practices.
3. Exploratory analysis of the data and setting of purposeful transformation.
4. Specification of the statistical outputs of the methods [10].

4. PREDICTION ANALYSIS IN THE DATA-MINING WORKSPACE

Rob Hyndman, Anne B. Koehler, J. Keith Ord, and Ralph D. Snyder [27] describe prediction analysis as a forecasting method with elaborate algorithms. *"A forecasting method is an algorithm that provides a point forecast: a single value that is a prediction of the value at a future time period. On the other hand a statistical model provides a stochastic data generating process that may be used to produce an entire probability distribution for a future time period n+h".*

Improvement of the prediction by experimental business approaches includes a set of improvement models on every stage and develops the capability to easily and quickly build the prediction models. In this chapter, it presents the several methods of forecasting the trend of export costs. Authors offer to focus on the methods: Exponential smoothing method, ARIMA method, neural networks method, and describe these methods as the best approaches to decision making. However, the main goal is to choose the proper process in forecasting.

The exponential method as operation method is used for smoothing and forecasting of time series values [15]. This method employs a linear combination. Exponential smoothing maintains that the weight decreases exponentially. This method can be used only for time series without trend and seasonal ingredients. The method uses the Holt-Winters smoothing, which has trend and seasonal ingredients. It contains three parameters: the level of α, β and γ for seasonal components (function Holt-Winters).

It assumed that in time n, which represents the observation of series of empirical values: $y_{n=k}$, k =0,1……. n-1, where different values are interpreted as observation time from point of view. Time series has the form:

$$y_{n-R} = T_{n-k} + \varepsilon_{n-k} \tag{1}$$

T_{n-R} – trends; n – moment in time that represents the observations in the present tense; R – observation time from point of view.

Trend time series is considered in short sections as constant. Relationship balancing the values of time series:

$$y_{n-R} = (1-\lambda) y_{n-R} + \lambda Y_{n-R-1} \tag{2}$$

An important part of exponential smoothing is to find the best constant λ. The constant is chosen such that it corresponds to the smallest mean square error [1 - 3, 5, 7, 15, 22, 33].

One of the econometric methods for the prediction of the statistical relationship between investigated parameters is ARIMA. Pankratz [21] noticed that: *"ARIMA models are convenient for producing forecasting of independent variable whenever an independent variable is contemporaneous* *with the dependent variable in an econometric model."* The method «ARIMA» (autoregressive integrating moving average) is a process in which changes have an unsystematic random character. These models describe an integrated process of random stochastic trends. The first difference of a series Y_t are presented by the equation $\Delta y_t = y_t - y_{t-1}$. If the series after first differencing is not stationary, we use the next equation $\Delta y_t = \Delta y_t - \Delta y_{t-1.}$ It is the method after the transformation process with integrated differential d-th order autocorrelation. Such results show that you can set the form of stationary model ARMA (p, q) or autoregressive models. Building models are produced by repeating the ARMA process. Generated stationary series is modelled by the ARMA model [1, 3, 6, 14, 21, 22]. The ARIMA model (p, d, q) will collectively be written as $\varphi\ (B)\ (1 - B)\ ^d y_t = (B)$. Where Autoregressive operator $v\ (B) = \varphi\ (B)\ (1 - B)^d$. The ARIMA model will predict future values $X_{T+h.}$ For this reason the model in the form of differential equations can be used. The integrated mixed ARIMA model (p, d, q) has the form: $(B)\ w_t = (B)$,

$$w_t = \Delta\ ^d y_t \tag{3}$$

where: d – the difference is modelled by process y_t, y_t – the stationary series of ARMA model (p, q) for the process [1, 6, 22].

Mun [17] characterizes modelling the ARIMA process thus. *"Properly ARIMA modelling requests testing of the autoregressive and moving average of the errors in the time - series data in order to calibrate the correct p, d, q inputs.*"

The neural network relates to progressive intelligence methods. It means to handle the amount of data that is characterized by a large number of interconnected processes and computing options. Differences of neural networks from other techniques is the ability to solve nonlinear problems with the architecture of the brain and the complex analysis of data. A neural network is a very useful tool in practice because it responds correctly to unknown inputs [30].

A neural network is a system of neurons interlinked by evaluated weights and having the ability to learn. In terms of application, we distinguish the input, the hidden and the output neurons. Processing of information on the network is enabled by changing the state of neurons between input and output neurons. The states of all neurons in the network define the states of synaptic weights of connections. The neurons represent the neural network configuration [4, 12, 20, 32 - 35].

Data mining workspace is a unique opportunity to follow the prediction process in one place. This advantage of the data mining workspace is suited for managers looking for faster ways for decision making. Data mining workspace allows in one workspace to regulate options and to manipulate with it. The authors use data mining areas as the mobile device to perform the comparison of the results and finally to decide: "What method optimises the model for future decisions within prediction systems?"

5. PREDICTION ANALYSIS IN THE DATA-MINING WORKSPACE

The favour of combining models is to compare the predicted abilities in several alternative models. The task of designing is to ensure the accuracy of the final result prediction. We used Data-Mining workspace (see fig. 1). All three prediction options, Exponential, ARIMA and Neural Network methods, have their place in the forecasting. This way helps to investigate the reaction of every method simultaneously in this case.

6. GRAPHS OF STATISTICAL OUTPUTS

From the previous steps provided, we got the next outputs of graph capture individual evaluating process. The methods allow a control of all-important features. Adaptation of methodologies carries out basic information about prediction behaviours. On the next pictures, we have reprehensive metrics of these methods (see figures 2-5).

Authors have created three statistical attempts for prediction purposes. The outputs of neural network obtained a good forecast diagram. The prediction model (1. MLP 12 - 8- 1) presents closeness between initial and predicted observations. It represents a favourable broad cross-section of input including historical data and output targets. Authors decided to continue the prediction analyses with the skills of the neural network. The neural network is a great way to get a standardized look at our forecasting. The forecasting from the neural network methodology fits a variety of different neural networks and in a suitable setting performs as the best model.

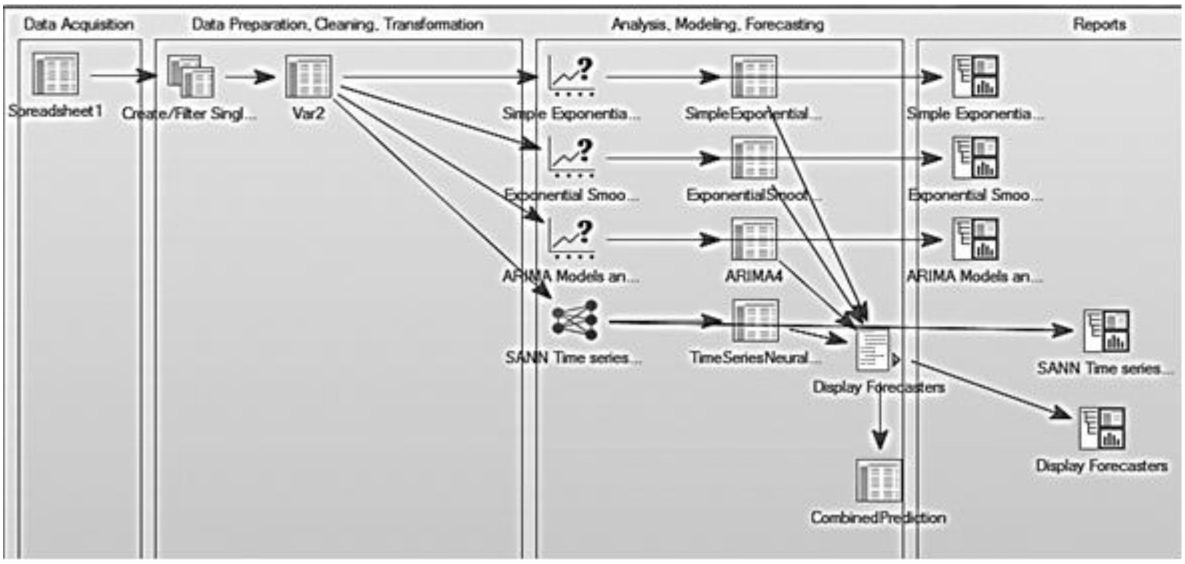

Fig. 1. Prediction methods in the data miner workspace. Source: Author's own
Рис. 1. Применение методов Data Mining для прогнозирования

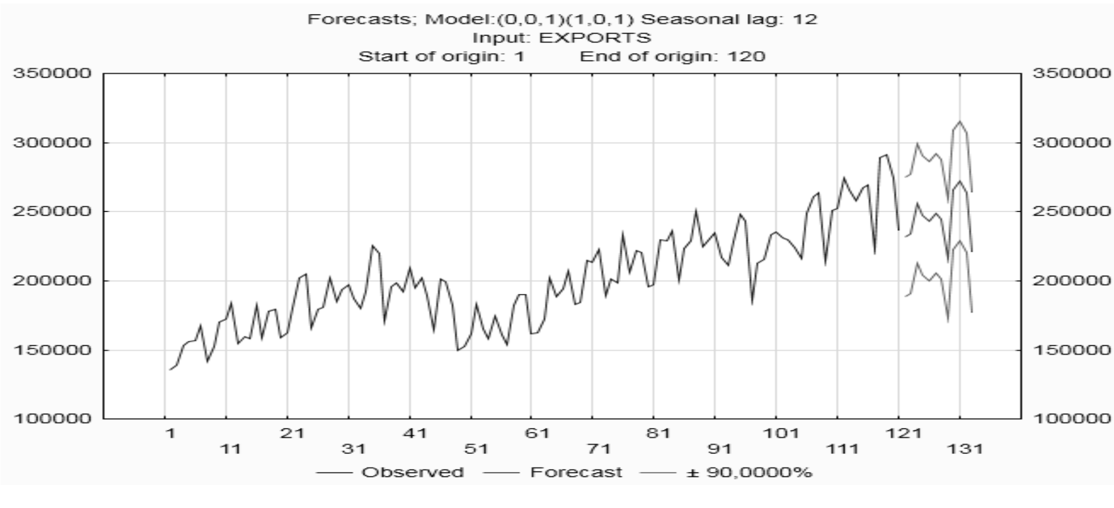

Fig. 2. ARIMA method for forecasting. Source: Output from the SANN program
Рис. 2. Применение метода ARIMA для прогнозирования

7. DISCUSSION

Time series for neural network move in a sequence of values is dependence on time t. The value in time t =1 we designate $x_{1,}$ v time t =2 we designate x_2 and value in time t =N we designate x_N, where N indicates the total number of values of the time series. Mathematically, it can be written as a vector x = (x_1, x_2,….. x_N). The value x_{N+1} will be the first value prediction configuration [8].

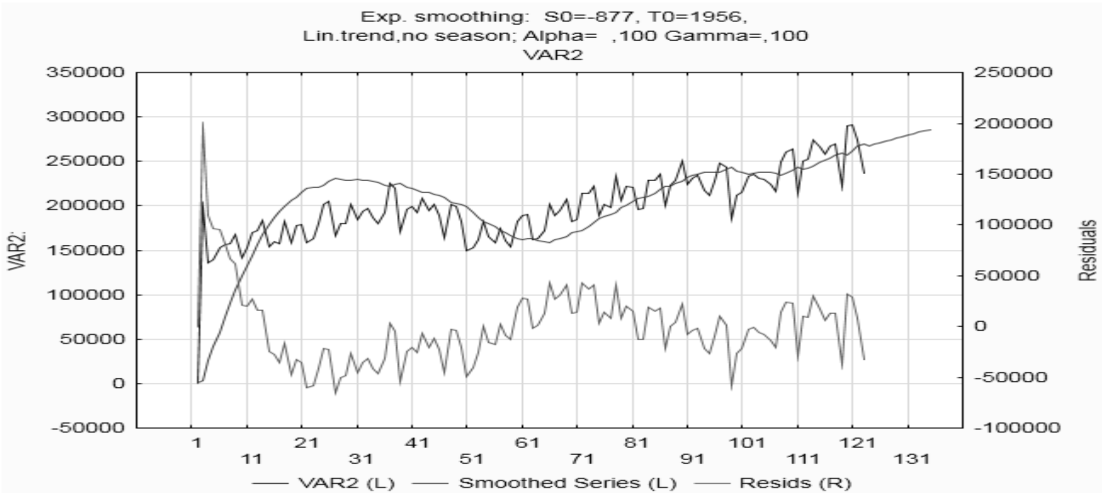

Fig. 3. Exponential smoothing method for forecasting. Source: Output from the SANN program
Рис. 3. Применение метода экспоненциального сглаживания для прогнозирования

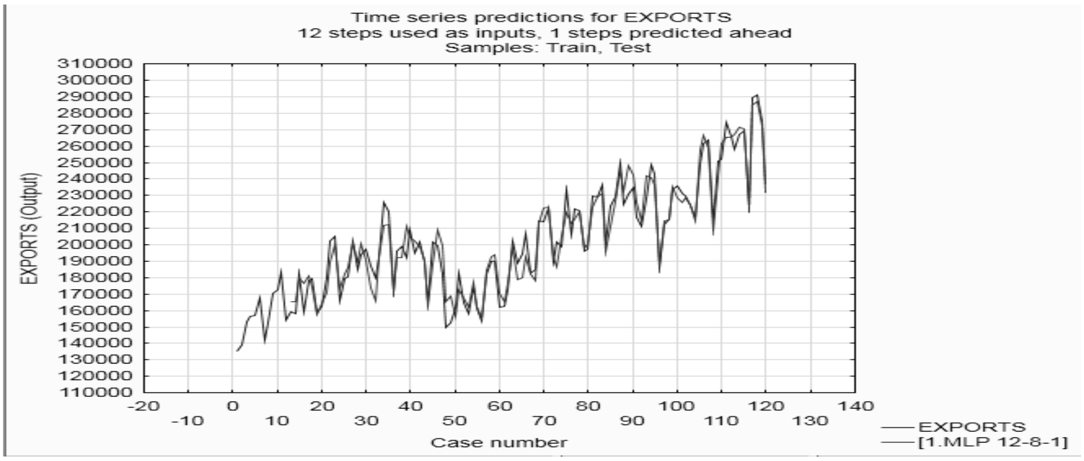

Fig. 4. Neural network method for forecasting. Source: Output from the SANN program
Рис. 4. Применение нейронных сетей для прогнозирования

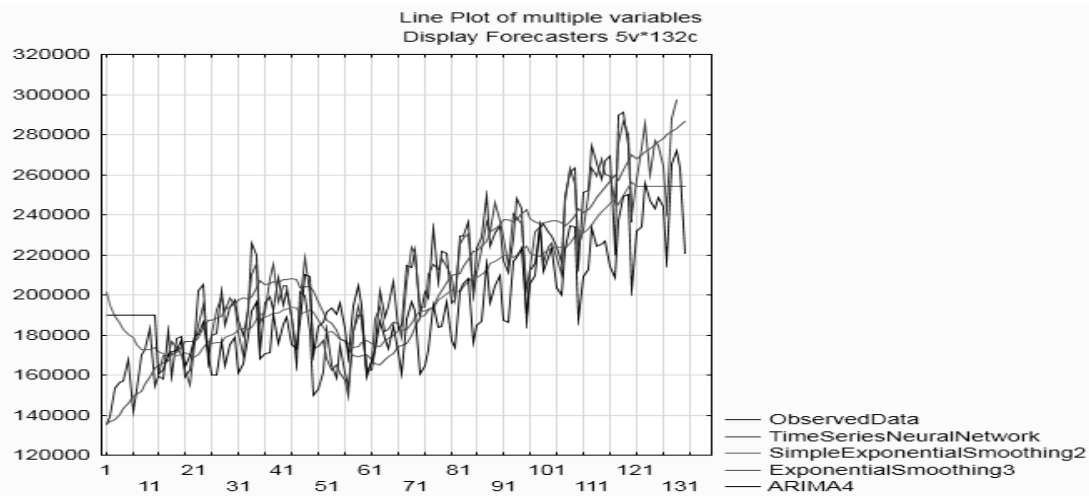

Fig. 5. Combining of prediction methods in the data miner workspace. Source: Output from the SANN program
Рис. 5. Использование конкретных методов прогнозирования

7.1. Methodology of time series prediction with using neural networks

The most important aspect of the neural network methodology is that it can be summarized in the following:

1. Choice of input data

An essential part of a neural network design is the selection of appropriate variables. The main task is to decide how much input neurons will be included in the model.

2. Specification of the requirements for the prediction accuracy

The prediction process follows the observations that obtain the raw data. A very important requirement is the evaluation of the quality prediction of the model, which is based on knowledge of the actual values. Various criteria are used for estimating whether the model behaves as it was planned. The most common using is to use MSE (the mean square error), MAE (the mean absolute error) and MAPE (the mean relative errors). MAPE is expressed:

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{x_t - \bar{x}_t}{x_t} \tag{4}$$

3. Selecting the appropriate model of neural network

We must examine the statistical characteristics of generated models and take into account the type of model that meets our requirements for finding the right solutions. This view is needed for the choice of the most suitable type of neural network.

4. Determining the training and validation data

An important capability of neural networks is an addiction of training algorithms because without decomposition testing the process cannot generate good quality neural network.

5. Optimization architecture for proposed neural networks

The most appropriate neural network architecture depends on the correct setting parameters. This step is one of the most difficult parts for the creation model [8, 19].

We can perform the model of prediction that is based on the principals of the neural network for the multilayer perceptron type. Fig. 6 explains the structure of neural network prediction.

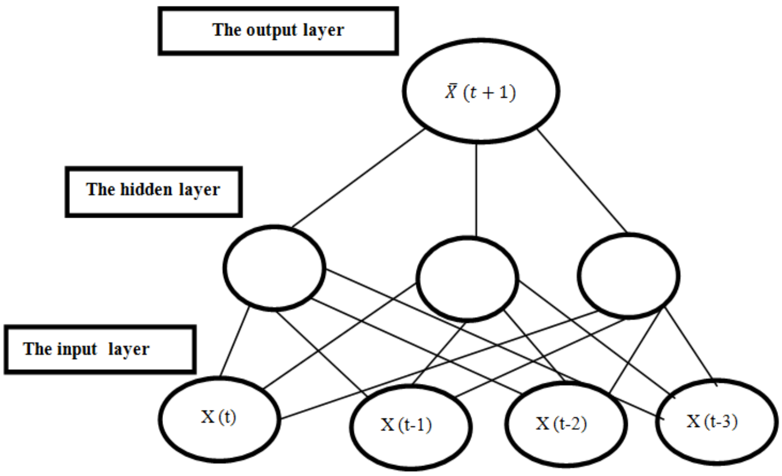

Fig. 6. Example of neural network for prediction. Source: Novák, M Beck, C.H. (1998)
Рис. 6. Пример использования нейронной сети для прогнозирования

7.2. Application of methodology neural networks

Applying data mining methodologies, it is important to understand the methods used and to choose the current best process-oriented approach. We solved to improve the capability of the neural network and we implemented the special steps for getting our prediction goals. We took attention on the next setting, where we dealt with 12 input neurons and we used a minimum of two hidden neurons and a maximum of eight hidden neurons. We illustrated the Next statistical characteristics for our five of generated models of neural networks in figures 7-9.

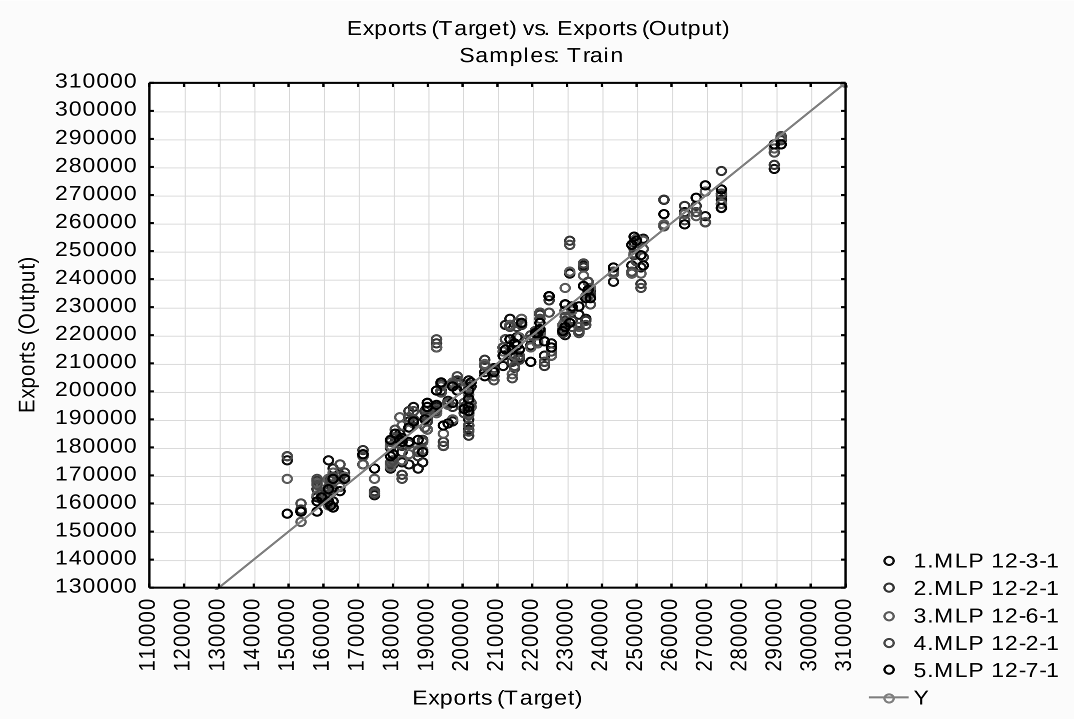

Fig. 7. The Versus Fits Plot of 5 neural network models. Source: Output from the SANN program
Рис. 7. 5 моделей прогноза с использованием нейронной сети

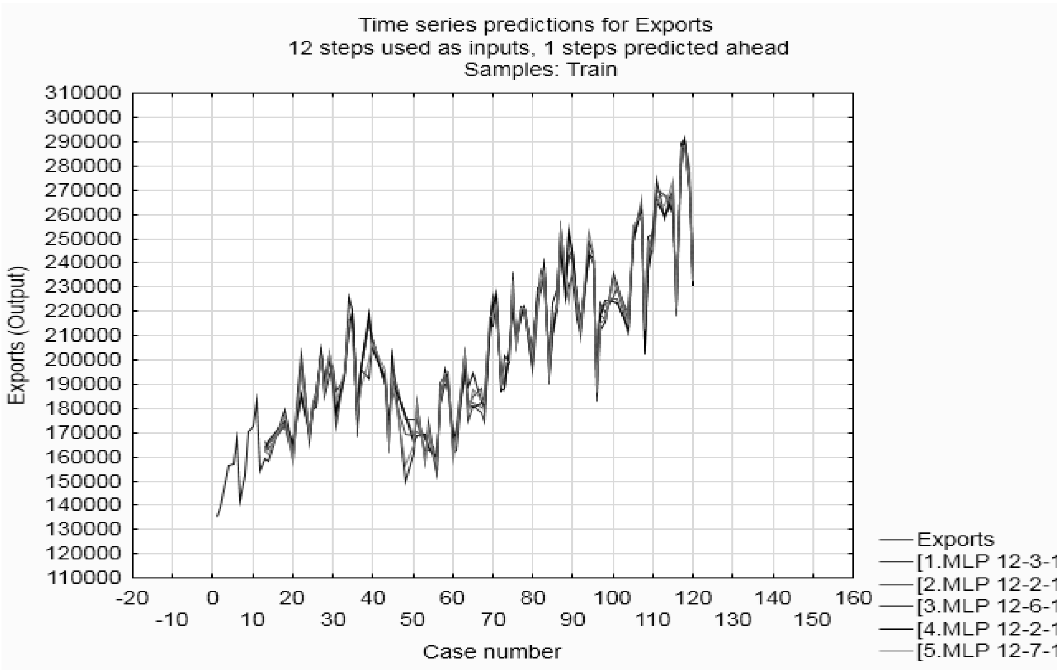

Fig. 8. Time series prediction of 5 neural network models. Source: Output from the SANN program
Рис. 8. Нейросетевые модели прогнозирования временных рядов

Statistics	1.MLP 12-3-1	2.MLP 12-2-1	3.MLP 12-6-1	4.MLP 12-2-1	**5.MLP 12-7-1**
Minimum prediction (Train)	157225,5	158128,9	153155,1	160050,8	156468,9
Maximum prediction (Train)	290176,6	289261,0	290530,1	291234,0	288349,2
Minimum prediction (Test)	156488,6	159249,4	163131,5	161984,1	161221,7
Maximum prediction (Test)	274839,4	272753,6	282923,4	275055,4	282923,0
Minimum prediction (Validation)					
Maximum prediction (Validation)					
Minimum prediction (Missing)					
Maximum prediction (Missing)					
Minimum residual (Train)	-25756,3	-26990,5	-23640,1	-27258,6	-9475,8
Maximum residual (Train)	15900,0	18159,8	13890,0	16531,7	10471,4
Minimum residual (Test)	-21745,2	-27216,8	-25987,0	-26950,2	-31824,6
Maximum residual (Test)	21268,1	17609,9	16686,5	16879,5	13359,4
Minimum residual (Validation)					
Maximum residual (Validation)					
Minimum standard residual (Train)	-5,6	-5,4	-5,8	-5,4	-3,4
Maximum standard residual (Train)	3,4	3,6	3,4	3,3	3,7
Minimum standard residual (Test)	-2,9	-3,6	-3,3	-3,5	-4,2
Maximum standard residual (Test)	2,8	2,3	2,1	2,2	1,8
Minimum standard residual (Validation)					

Fig. 9. Prediction statistics of five neural networks models. Source: Output from the SANN program
Рис. 9. Статистическая значимость нейросетевых моделей прогнозирования

The results were generated under the following principles of neural network (it is described in figure 6.) From the discovering patterns of generated characteristics, we acquired the prediction model 5 MLP 12-7-1, which for us is more suited. Table 1 illustrated our calculation of mistake MAPE. This is the last stepping to judge the quality of the model.

Table 1

Calculation MAPE using the neural network 5 MLP 12-7-1

Forecas-ting method	**Months**	**t**	x_t	$\bar{x}_t$	$\frac{x_t - \bar{x}_t}{x_t}$	$\sum_{t=1}^{N} \frac{x_t - \bar{x}_t}{x_t}$	$\frac{1}{N}\sum_{t=1}^{N} \frac{x_t - \bar{x}_t}{x_t}$	$MAPE = \frac{100}{N}\sum_{t=1}^{N} \frac{x_t - \bar{x}_t}{x_t}$
Neural network methods	Feb.2014	1	252140	251056,8	0,004296026	0,095033	0,007919	0,79%
	Mar.2014	2	274333	265187,3	0,033337951			
	Apr.2014	3	266102	262076	0,015129537			
	May.2014	4	257865	259032	-0,004525624			
	Jun.2014	5	266930	263984,6	0,011034354			
	Jul.2014	6	269412	260442,4	0,033293246			
	Aug.2014	7	222508	228446,1	-0,02668713			
	Sep.2014	8	289506	285228,7	0,014774478			
	Oct.2014	9	291325	291234	0,000312366			
	No.2014	10	274632	270768,6	0,014067552			

Source: Author's own.

8. CONCLUSION

This article suggested the general overview of the prediction methods that with their statistical outputs make for effective processing in future. The aim of the paper is to expand the existing prediction methods for improving prediction in the process modelling. The object of the work is to do prediction performance more attractively and make the modelling process easier. The task is to verify the application of the methods within linkage between historical data and future data for time-series prediction. The authors offer to work in the data mining workspace and to describe this tool as fast and convenient for decision making. Obviously, from the distinction between the observed results, the authors’ offer to use advanced technique is as a neural network tool of artificial intelligence. The transformation of inputs in terminal output supported by the neural network method shows that it would better demonstrate the predictive power of the structural model. The applied device estimates the most generated structural models. From the statistical characteristics of the generated data, the authors selected the model of 5 MLP 12-7-1. This model defines the mean relative error in the 0,79% and progresses as one of the ideal types of neural network for future decision making in the transport problems relating to prediction.

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