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COMPARISON OF TIME SERIES FORECASTING WITH ARTIFICIAL NEURAL NETWORK AND STATISTICAL APPROACH

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Abstract

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In this paper we concentrate on prediction of future values based on the past course of a variable. Traditionally this problem is solved using statistical analysis – first a time-series model is constructed and then statistical prediction algorithms are applied to it in order to obtain future values. The time series modelling is a very powerful method, but it requires knowledge or discovery of initial conditions when constructing the model.
The experiment described in this paper consists of a comparison of results computed by Multi-layer perceptron network with different learning algorithms previously published and results computed with different types of ARMA models. For the network configuration an analytical approach has been applied through the cross-validation method. We performed an exact comparison of both approaches on real-world data set. Results of two types of artificial neural network learning algorithms are compared with two algorithms of statistical prediction of future values.
The experiment results are later discussed from several different points. First the comparison is focused on output precision of both approaches. The comparison consists of matching neural networks results and real values on few steps of prediction. Then the results of ARMA models are compared with real values and conclusion is made. The conclusion also includes theoretical and practical recommendations.

artificial neural networks, time series forecasting, statistical approach, comparison study

The aim of the article is comparison of real data forecast using statistical methods and artificial neural network (ANN). Traditionally, different methods of statistical analysis are fixed part of the decision process in the economical resolution (Husek, 2007) (Meloun, Militký, 2004). An artificial neural network offers a kind of intelligent automation of the decision process where the variants of solutions are prepared. Also the principle of ANN is different to statistical models. The ANNs are much less sensitive to input conditions. These points justify the increasing number of successful real-world applications of ANN in business.

ANN is one of the Artificial Intelligence (AI) methods. These are used to solve tasks where the standard approach is not effective or impossible. The main areas of AI applications are forecasting, classification and optimization. Actual applications of ANN include the usage in Management Information systems (Wenlichová, Štencl, 2009), or classification in evaluation of consumer behaviour (Wenlichová, Fejfar, 2010). In a broader application area, the implementation of various machine-learning algorithms as part in development of search engines for geodetic data (as published by Procházka (2010)).

The comparison of methods described in this article is related to a previously published paper (Štencl, Šťastný, 2010), which was focused on optimization of the ANN's learning process. Both papers are part of a comparison study focused on forecasting of real-world economical values with artificial intelligence methods. This article describes the comparison performed on real datasets containing Czech household consumptions expenditures.

There are many problems associated with the analysis of economic data. A problem that is most often experienced (especially in Czech national conditions) is the length of economical time series. It very often consists of small number of observation (typically tens of units) or has a missing data inside the data set. Solving both of these problems is the key part of prediction with all known methods. We believe that the mechanism of the ANN allows qualitatively good forecast even on small sized data sets.

Previous experiments (Štencl, Šťastný, 2010) (Šťastný, Škorpil, 2005) were focused on the comparison of learning algorithm because of the efficiency of learning process. Such optimizations of the learning process often cost the output precision. This paper compares the forecast quality of both predictions made by MLP networks with statistical ARIMA methods. For better orientation in the methods used, a brief Levenberg-Marquardt learning algorithm description is included.

METHODS AND RESOURCES

The experiment consists of comparison of results computed by Multi-layer perceptron network with different learning algorithms (Štencl, Šťastný, 2010) and results computed with different types of ARMA models. For the network configuration an analytical approach has been applied through the cross-validation method.

Neural networks methods

A multi-layer perceptron (MLP) network is one of the most widely used methods for time series forecasting. While MLP networks are basic models of the artificial neural networks, they generally provide qualitatively strong results.

When working with MLP networks, the most important step is the learning process. Several different learning algorithms can be used. The best-known algorithm is the back-propagation algorithm. A more detailed description was previously published (Štencl, Šťastný, 2010). We will make only brief comment about the Levenberg-Marquardt learning algorithm as it is thoroughly described in (Štencl, Šťastný, 2010).

Levenberg-Marquardt learning algorithm

The Levenberg-Marquardt (LM) learning algorithm is one of the fastest learning algorithms for MLP networks (Hagan, Menhaj, 1999). The LM algorithm is a variant of the Gauss-Newton method and was designed to approach second-order training speed without having to compute the Hessian matrix (Hagan, Menhaj, 1999). Typically, for the learning of feed-forward neural networks, a sum of squares is used as the performance function. Then the Hessian matrix can be approximated as

$$H = J^T J$$

and the gradient can be computed as

$$g = J^T e,$$

where J is the Jacobian matrix that contains first derivate of the network error with respect to the weights and biases, and e is a vector of network errors (Hagan, Menhaj, 1999) (Sotirov, 2002).

ARMA models

Autoregressive moving average (ARMA) models are part of the Box-Jenkins methodology for time series forecasting (Wedding, Cios, 1995). Box-Jenkins methodology is based on three consecutive steps:

1. **Identifying the tentative model**

This involves identification of the model into the category determined by making the data stationary (usually by differencing the data) and then analysing the autocorrelations and partial autocorrelations of the stationary data. Model identification examines a wide variety of possible models including autoregressive terms, moving average of past error terms in order capture a myriad of past data patterns and to postulate a potential forecasting model.

2. **Determining the parameters of the model and verification**

This is similar to estimating the parameters in regression analysis. For determining adequacy of the model, different statistical tests are applied.

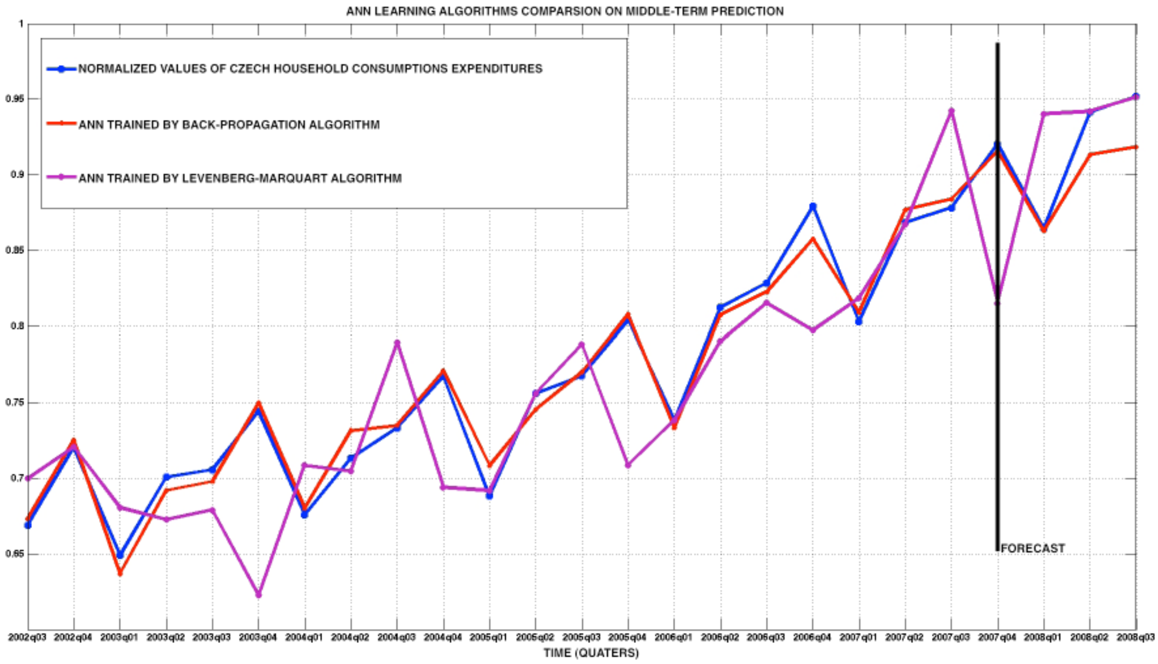
3. **Forecasting with the model**

When final model is determined to be adequate (random error terms), the forecast period is established. Both point and interval forecasts are provided.

Czech household consumptions expenditures dataset

Household consumption expenditures are recorded using internationally standardised COICOP "Classification of Individual Consumption by Purpose" methodology[1]. The resulting models contain a large number of variables that cause a strong non-linear increase in complexity of its analysis. Another problem is notable incompletes and uncertainty in the datasets. In long term view there is an apparent pursuit to connect information technologies based on artificial intelligence with traditional approaches of economic analysis based on purely mathematical models.

1 Available at <http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/themes>



1: *ANN Learning Algorithms comparison*

Dataset for experiment represents Czech household consumption expenditures includes values between years 2001 and 2008 measured quarterly. The dataset consists of twelve main indexes of household consumption expenditures[2] and standardised time series computed using the COICOP methodology. The dataset is obtained from statistical database; values are in thousands of Czech crowns (CZK).

RESULTS

First part of the experiments was published by Štencl and Šťastný (2010) and was focused on learning algorithms comparison. Graphical results are shown on Fig. 1. The experiment was performed through Matlab R2010a environment with dataset of 28 quarterly measured values of Czech household expenditures. Both approaches brought good results measured by the output precision. Next step was the comparison experiment with the selected statistical model.

ARMA experiments

The X-12-ARIMA[3] method is implemented as an extension to Gretl software package (Rosenblad, 2009). Simply described, it automatically creates a time-series model using the Box-Jenkins methodology, which is then used to predict values for given periods.

The X-12-ARIMA method is an alternative to constructing ARMA models using native code. It is actively developed by U.S. Census Bureau[4] and is being used for seasonal adjustment of time series. The Gretl software package contains X-12-ARIMA module (Rosenblad, 2009), which is capable of using an external X-12-ARIMA application. After the seasonal adjustment is made, the data are returned back to the Gretl software for further analyses. Gretl will automatically choose a suitable time-series model according to analysis performed and seasonal adjustment of the input time-series. Apart from the result analysis, the output contains also prediction values for defined periods.

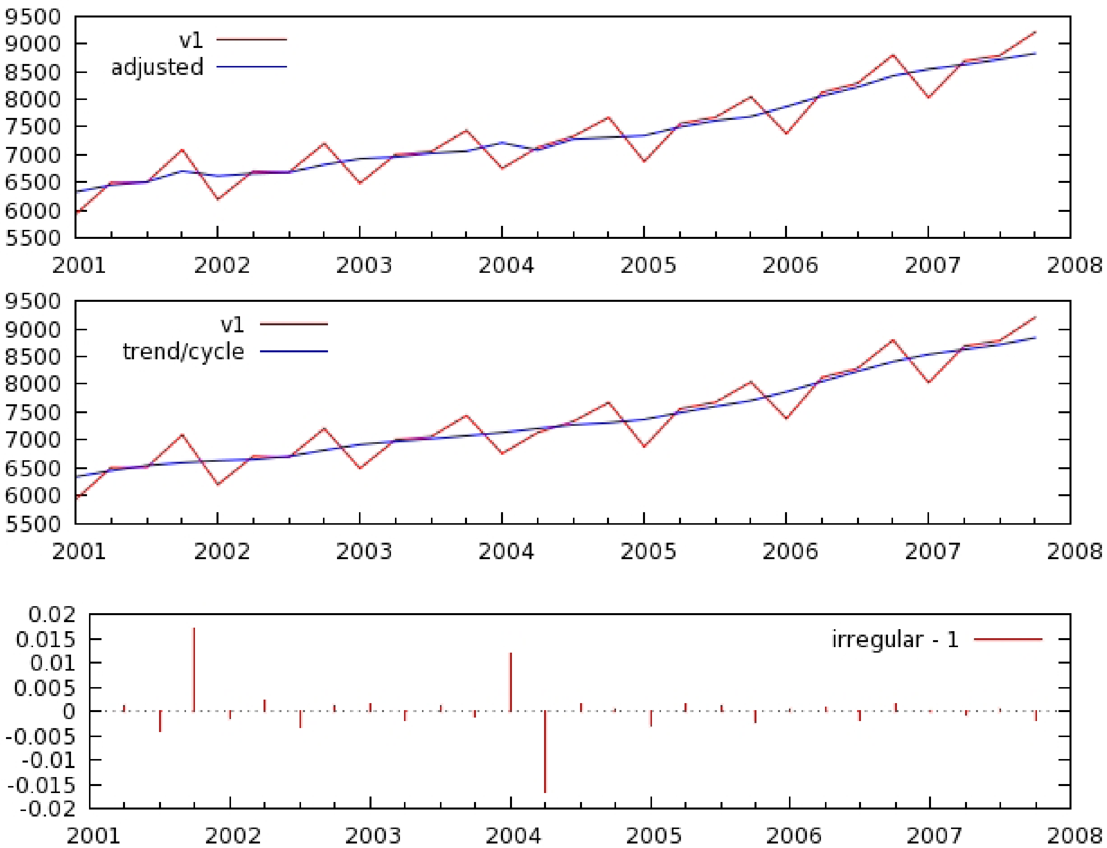
Experiment 1: household expenditures statistics

Using the methods described above we have first performed a standard analysis in the Gretl software (Table I). Then we performed an automated analysis using the X-12-ARIMA method. The input time-series represents household consumption expenditures data.

Using the X-12-ARIMA method we have performed an analysis of the trends of the input time-series and both cyclic and random components of the time-series were identified.

Fig. 2 shows three graphs. In all graphs, the red line represents values of the original time-series data and the blue line shows the time-series with adjusted random component (first graph) and with removed seasonal component (third graph).

2 Available at <http://ec.europa.eu/consumers/index_cs.ht>
3 Available at <http://www.census.gov/srd/www/x12a/>
4 Available at < http://www.census.gov>



2: *ARIMA seasonal adjustment and trend analysis*

I: *Prediction of household consumption expenditures using the ARIMA model*

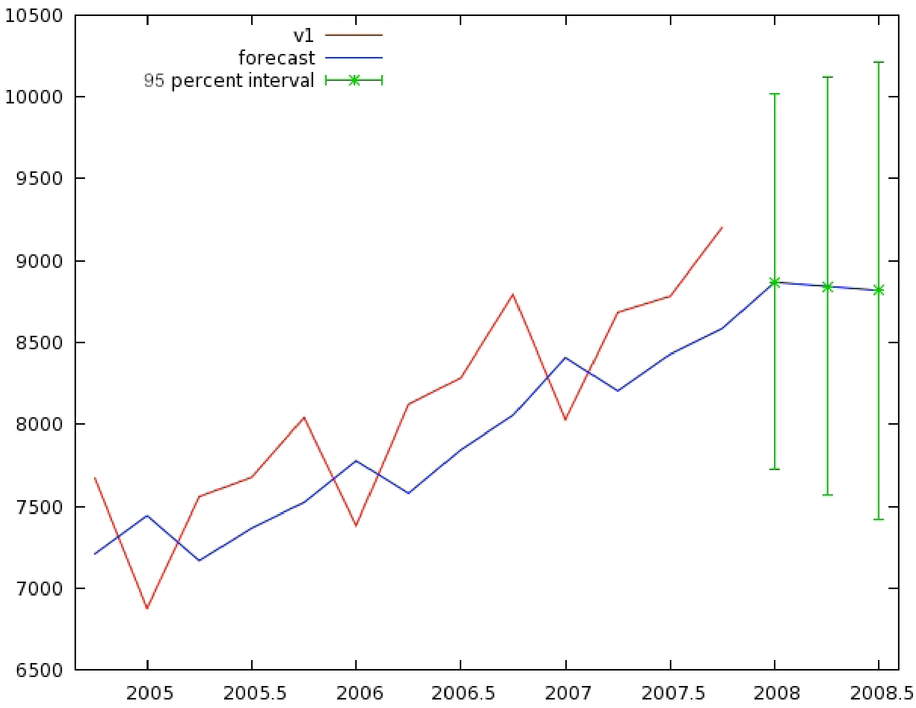
Period	Value	Standard Error	Confidence Interval (95%)	
			lower	higher
2008/Q1	8870.04	445.357	7722.87	10017.20
2008/Q2	8844.51	496.357	7565.98	10123.04
2008/Q3	8819.47	540.894	7426.22	10212.72

II: *Prediction of household consumption expenditures*

Period	Value	Standard Error	Confidence Interval (95%)	
			lower	higher
2008/Q1	8464.19	108.460	8251.62	8676.77
2008/Q2	9112.98	133.251	8851.81	9374.15
2008/Q3	9213.05	158.756	8901.89	9524.20

III: *Comparison of the prediction using statistical models and neural networks*

Period	Real value	ARIMA	X-12-ARIMA	MLP network	
				BP	LM
2008/Q1	8647.00	8870.04	8464.19	8630.06	9404.00
2008/Q2	9417.00	8844.51	9112.98	9134.15	9421.70
2008/Q3	9521.00	8819.47	9213.05	9185.76	9513.60



3: *ARIMA forecast*

The time-series adjustment was performed using multiplicative seasonal adjustment. X-axis on the graph (Fig. 2) shows absolute values of the time-series. Y-axis represents quarters of the monitored years. Second graph show predicted trend of the time-series. Last graph identifies random component of the time-series.

The prediction was constructed for 3 quarters of year 2008. Confidence level was set to 95%. During the analysis, 5 iterations of the ARIMA model were run; each analysis performed 7 function searches. Table II shows the prediction results using the automated X-12-ARIMA method, which in this case performs better.

The values computed using statistical analysis; have to be compared to results of neural network experiments. The comparison is shown in table III. Predicted values closest to real values are bolded. Better results of the X-12-ARIMA in the last quarter are probably caused by generally undervalued trend of the time-series.

Results of the experiments are comparable in terms of prediction accuracy. Some of the expected differences were proofed. The first difference is that both statistical methods computed worse results, when compared to the neural networks results. The cause could be the type of the prediction – focusing on precise point prediction. The principle of the statistical methods is based on averaging. The figures 1 and 3 shows good example. On figure 1 both neural networks are approximating target data with defined error. Figure 3 shows the statistical progress (based on averages) resulting as slightly undervalued.

We can conclude that it is better to retrieve the results for short time prediction with MLP-NN when comparing with the automated ARIMA implementation. The result is based on the methods principles comparison. Obtained forecast results of the MLP-NN copying the real data more precisely that in the case of ARIMA automated models. Future work will focus on testing of other types of ANN.

SUMMARY

In this paper we concentrate on prediction of future values based on the past course of a variable. Traditionally this problem is solved using statistical analysis. The time series modelling is a very powerful method, but it requires knowledge or discovery of initial conditions when constructing the model. The experiment described in this paper consists of a comparison of results computed by Multi-layer perceptron network with different learning algorithms previously published and results computed with different types of ARMA models. We performed an exact comparison of both approaches on real-world data set. Results of two types of artificial neural network learning algorithms are compared with two algorithms of statistical prediction of future values.

Comparison result shown better ability of Multi-layer NN for short time prediction as used automated ARIMA models. From learning algorithms used in the experiment, the Back-propagation learning

algorithm proofed very good ability for short-term prediction. Future work will focus on testing of other types of ANN.

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REFERENCES

HAGAN, M. T., MENHAJ, M., 1999: Training feedforward networks with the Marquardt algorithm, IEEE Transactions on Neural Networks, Vol. 5, No. 6, 1999, pp. 989–993.

HUSEK, R., 2007: Ekonometrická analýza. 1st edition. Praha: Oeconomica. 2007, pp. 368. ISBN 978-80-245-1300-3. In Czech.

MAŘÍK, V., ŠTĚPÁNKOVÁ, O., LAŽANSKÝ, J. a kol., 2003: Umělá inteligence. 1st edition. Sv. 1. Praha: Academia. ISBN 80-200-0496-3. In Czech.

MELOUN, M., MILITKÝ, J., 2004: Statistická analýza experimentálních dat. 2nd edition. Praha: Academia. 2004, pp. 953. ISBN 80-200-1254-0. In Czech.

PROCHÁZKA, D., 2010: On development of search engine for geodata. Acta Universitatis agriculturae et silviculturae Mendelianae Brunensis. Sv. 6/2010, č. LVIII, pp. 389–397. ISSN 1211-8516.

ROSENBLAD, A., 2009: Gret1 1.7.3. Journal of Statistical Software, Software Reviews. Vol. 25. N. 1. pp. 1–14 (2009). [online] [cit. 2010-11-22]. Available at <http://www.jstatsoft.org/v25/s01>.

SOTIROV, S., 2002: A Method of Accelerating Neural Network Learning, Neural Processing Letters, Vol. 22, pp. 163–169. ISSN 1370-4621.

ŠTENCL, M., ŠŤASTNÝ, J., 2010: Neural network learning algorithms comparison on numerical prediction of real data. In: MENDEL 2010, 16th International Conference on Soft Computing. Brno: Brno University of Technology, 2010, pp. 280–285. ISSN 1803-3814.

ŠŤASTNÝ, J., ŠKORPIL, V., 2005: Neural Networks Learning Methods Comparison, International Journal WSEAS Transactions on Circuits and Systems, Issue 4, Volume 4, pp. 325–330, ISSN 1109-2734.

TSENG, F. M., YU, H. C., TZENG, G. H., 2002: Combining neural network model with seasonal time series ARIMA model. Technological Forecasting and Social Change, 69, 71–87.

WEDDING, D. K., CIOS, K. J., 1995: Time series forecasting by combining RBF networks, certainty factors, and the Box-Jenkins model, Neurocomputing, Vol. 10, pp. 149–168. DOI: 10.1016/0925-2312(95)00021-6.

WEINLICHOVÁ, J., FEJFAR, J., 2010: Usage of self-organizing neural network in evaluation of consumer behaviour. Acta Universitatis agriculturae et silviculturae Mendelianae Brunensis. Sv. 6/2010, č. LVIII, pp. 625–631. ISSN 1211-8516.

WEINLICHOVÁ, J., ŠTENCL, M., 2009: Artificial Neural Networks in Management Information Systems. Acta Universitatis agriculturae et silviculturae Mendelianae Brunensis. Sv. 6/2009, č. LVII, pp. 331–334. ISSN 1211-8516.

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