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A COMPARISON OF FORECASTING THE RESULTS OF ROAD TRANSPORTATION NEEDS

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Abstract. Determining the size and quality of transport needs would not be possible without adequate forecasting based on the sales volume or demand for this service from the past periods. Traditional forecasting methods use econometric models that may be subject to serious errors. The use of the methods taking into account the variability of the studied phenomena or more advanced mathematical methods enables to minimize the error. Various methods of artificial intelligence such as a neural network, fuzzy sets, genetic algorithms, etc., have been recently successfully applied. The aim of this paper is to compare three forecasting methods that can be used for predicting the volume of road freight. The article deals with the effectiveness of three prediction methods, namely Winter's method for seasonal problems – a multiplicative version, harmonic analysis and harmonic analysis aided by the artificial immune system. The effectiveness of prediction was counted using MAPE errors (main average percentage error). The results of calculations were compared and the best example was presented.

Keywords: road, transportation, forecasting, Winter's method, harmonic analysis, artificial intelligence, artificial immune systems, clonal selection.

1. Introduction. Literature Review

Forecasting is a widely described issue in literature. Forecasts can be used for determining the size of sales, future demand or transportation needs. The object of forecasting in most cases is a social, economic or enterprise system. Determining the size and quantity of transport needs would not be possible without adequate forecasting based on the sales volume or demand for this service from the past periods. The latter one as well as many other processes in the logistics of transport can be modeled using one or multidimensional time series.

Literature provides that prediction can be determined as a rational scientific process of future events. Dittmann (2008) discusses the importance of forecast for management and prediction process itself and describes the most commonly used forecasting methods, including:

- time series methods;
- econometric methods;
- analog prediction;
- qualitative methods.

Miscellaneous statistic methods that have been used for forecasting since 1980 have also been discussed in paper by De Gooijer and Hyndman (2006). Fourier coefficients were used for approximate nonlinearities in time series data and were debated by Ludlow and Enders (2000). Literature proposed two basic approaches to prediction, namely quantitative and qualitative, and presented the role of forecasts in the market economy (Nowak 1998).

The authors (Jóźwiak, Podgórski 2009) have described the components of time series methods and referred to the alignment of time series analysis and seasonal changes in prediction. The basic indicators of dynamics effects have been discussed.

Owing to this review, it can be also accepted that traditional forecasting models are using econometric models which, in the one-dimensional form, assume the form of the determined function. Such methods may be subject to a large-scale error. Adaptive methods, taking into account the variability of the studied phenomena, seem to be better. In this case, Winter's method is one of those. More advanced mathematical methods such as harmonic analysis have been also applied.

More advanced forecasting methods are based on artificial intelligence (AI). Those commonly known by researchers are (Ludwig *et al.* 2009):

- neural networks;
- genetic algorithm;
- fuzzy sets.

In the paper by Karlaftis and Vlahogianni (2011), the authors compare two ways of data analysis considering transport problems. Statistic and computational intelligence (CI) methods are considered. CI methods are better for solving problems with complex and non-linear data. The applications of neural networks were widely discussed.

In next research (Shih, Chung 2008), the authors present a hybrid artificial intelligent sales forecasting model of daily fresh foods for the convenience store. Two neural networks are used for building a hybrid artificial model.

The genetic algorithm applied to predicting seasonal demand is presented in paper by Chodak and Kwaśnicki (2002). The authors introduce a specific form of a demand function. The same method and other demand function were used for forecasting demand for the Internet shops (Chodak 2009).

Logarithm support vector regression was used for forecasting the concentrations of air pollutants in Taiwan (Lin *et al.* 2011). The coefficients of the regression function were calculated referring to artificial immune systems. The value of the main average percentage error (MAPE) was a measure of affinity between antibody and antigen. The results obtained using the artificial immune system were promising. Minimal MAPE was 17.06916%. The findings were compared with the results obtained by means of three other methods – general regression neural networks, seasonal autoregressive integrated moving average model (SARIMA) and back propagation neural networks.

The forecast of urban traffic flow has been prepared by Hong *et al.* (2011). In order to solve the problem, support vector regression (SVR) was used. Consequently, the hybrid genetic algorithm – simulated annealing algorithm GA-SA, was applied to receive an optimal parameter combination for it. Owing to the findings, the results are more adequate in the developed model than those in Holt and Winter's methods, autoregressive integrated moving average (SARIMA) or back-propagation neural network (BPNN).

The rough set theory was applied to predict the acquisition of a Greece firm in the paper by Słowiński *et al.* (1997). This theory is used for finding financial information tables of lower and upper approximation and helps with taking optimum financial decisions.

The use of fuzzy transformation for forecasting is presented in research carried out by Di Martino *et al.* (2011).

In order to obtain forecast, influential variables and sales volume are input in the adaptive network based on a fuzzy inference system developed by Wanga *et al.* (2011). Consequently, the developed model is compared with the autoregressive integrated moving average model ARIMA and the artificial neural network.

AI and traditional methods can strongly support the forecasting process. However, the methods based on AI should provide significantly better results. This is due to higher precision of computations in comparison to those methods performed manually by humans. As a result, using artificial intelligence systems should support the growth of adjustment results.

2. Prediction Analysis of Freight Volume Applying Prognostic Methods

A great number of human needs are associated with conveyance and related to the functioning of the entire national economy of each country. The current technological, economic and social development has created the need to deliberately organize the movement of cargo by means of transport. One of the most popular types of freight transport is road transport. The popularity of car transport depends primarily on the following characteristics:

- high efficiency;
- timing;
- ability to reach consumers in a variable location;
- high speed of transportation;
- possibility of delivering directly to the recipient without the need to reload in transit.

Due to this fact, research will be focused on forecasting the volume of freight conveyed by road transport.

In Poland, the total value of goods transported every year is growing. However, it is crucial to take into account the nature of road freight transport that depends on seasonality and relates to the weather and decisions made by manufacturers, which diminish the quantity of manufacturing goods in the last and first quarter of the year. This in turn translates a variable amount of transported goods in the subsequent quarters each year. Up to the third quarter, the quantity of transported goods grows every year. In the middle of the third quarter, growth stops and follows a downward trend until the middle of the first quarter of the next year. In case it is over, the whole cycle repeats.

Road transport is also influenced by the policy formulated by the national government, changes in regulating customs between countries, opening new markets (import, export) and the global economic situation. The less stable is the status of economy, the deeper may be slumps between successive years.

It can be seen that, for example, in 2006 and 2007, seasonality almost disappears. The volume of transportation needs in 2007 is lower than that in the previous year. A lower decrease in demand for the late fourth quarter of 2007 and the first quarter of 2008 can be noticed, which means that investors do not take any drastic decisions because of anxiety on the market.

Although in 2008 there is an increase in demand for road transportation needs, it can be found its size is generally small. 2009 is the year of a global economic crisis and a more drastic decline in transported needs can be noted. It is related to the fragility of entities and a more conservative attitude to business. Therefore, a seasonal decline in the volume of goods transported by road was reduced due to the market anxieties and felt to the lowest level in 2007.

In 2010, economy recovered slightly and, as a result, a minimal increase in the amount of transported goods in comparison to the previous year was recorded. However, growing declines in the seasonal pattern related to the crisis are noticeable.

Data concerning the freight volume of road transport were collected from the Central Statistical Office of Poland (Polska – wskaźniki… 2011). With reference to data analysis, the following prediction methods were chosen:

- Winter's seasonal method – a multiplicative version;
- harmonic analysis;
- harmonic analysis aided by the artificial immune system.

Fig. 1 presents data containing information about the volume of freight road transport in Poland for the period 2004–2009.

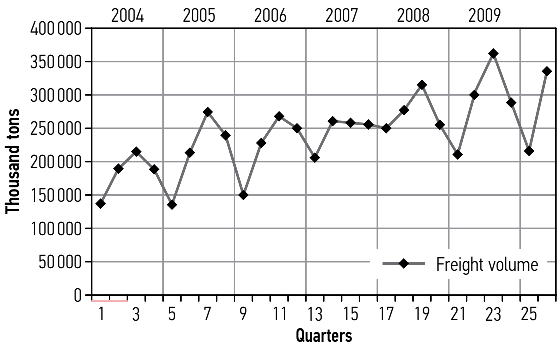

Fig. 1. Freight volume in thousand tons

The main purpose of the study is to compare forecasting results between the selected methods. The effectiveness measure will be calculated by the commonly used forecast error.

2.1. Seasonal Winter's Method

The formulas used for forecasting in the Winter's model are presented below (Dittmann 2008):

- forecast for the future periods, when $t > n$:

$$y_t^* = \left(F_n + (t-n)\cdot S_n\right)\cdot C_{t-r}; \tag{1}$$

- forecast for the future periods, when $t < n$:

$$y_t^* = \left(F_{t-1} + S_{t-1}\right)\cdot C_{t-r}; \tag{2}$$

- a smoothed evaluation of the average value level for time period t – 1:

$$F_{t-1} = \alpha\cdot\frac{y_{t-1}}{C_{t-1-r}} + (1-\alpha)\cdot\left(F_{t-2}+S_{t-2}\right); \tag{3}$$

- a smoothed value of trend growth for time period t – 1:

$$S_{t-1} = \beta\cdot\left(F_{t-1}-F_{t-2}\right) + (1-\beta)\cdot S_{t-2}; \tag{4}$$

- the evaluation of the seasonality index for time period t – 1

$$C_{t-1} = \gamma\cdot\frac{y_{t-1}}{F_{t-1}} + (1-\gamma)\cdot C_{t-1-r}, \tag{5}$$

where: F_t – a smoothed evaluation of the average value level for time period t; S_t – a smoothed value of trend growth for time period t; C_t – the evaluation of the seasonality index for time period t; F_n – a smoothed evaluation of the average value level for n = 24; S_n – a smoothed value of trend growth for n = 24; t – the number of the time period; n – the number of observation; α – a smoothing parameter of the level predicted variable; β – a smoothing parameter related to growth trend; γ – an evaluation parameter of the seasonality index; r – the length of the seasonal cycle.

2.2. Harmonic Analysis

The issue of harmonic analysis will be written as a sum of harmonics (Zeliaś *et al.* 2004):

$$y_t = f(t) + \sum_{i=1}^{\frac{n}{2}}\left(\alpha_i\cdot\sin\left(\frac{2\cdot\pi}{n}\cdot i\cdot t\right) + \beta_i\cdot\cos\left(\frac{2\cdot\pi}{n}\cdot i\cdot t\right)\right), \tag{6}$$

where: $f(t)$ – trend function; n – the number of the month; i – the number of harmonic; t– the number of the time period; α_i, β_i – coefficients.

The trend function was solved separately using the method of least squares. The estimated model of harmonic analysis can be defined as:

$$\begin{aligned}
\widehat{y}_t &= 167143.18 + 5765.15\cdot t +\\
& a_1\cdot\sin\left(\frac{2\pi}{24}\cdot t\right) + b_1\cdot\cos\left(\frac{2\pi}{24}\cdot t\right) +\\
& a_2\cdot\sin\left(\frac{2\pi}{24}\cdot 2\cdot t\right) + b_2\cdot\cos\left(\frac{2\pi}{24}\cdot 2\cdot t\right) +\\
& a_3\cdot\sin\left(\frac{2\pi}{24}\cdot 3\cdot t\right) + b_3\cdot\cos\left(\frac{2\pi}{24}\cdot 3\cdot t\right) +\\
& a_4\cdot\sin\left(\frac{2\pi}{24}\cdot 4\cdot t\right) + b_4\cdot\cos\left(\frac{2\pi}{24}\cdot 4\cdot t\right) +\\
& a_5\cdot\sin\left(\frac{2\pi}{24}\cdot 5\cdot t\right) + b_5\cdot\cos\left(\frac{2\pi}{24}\cdot 5\cdot t\right) +\\
& a_6\cdot\sin\left(\frac{2\pi}{24}\cdot 6\cdot t\right) + b_6\cdot\cos\left(\frac{2\pi}{24}\cdot 6\cdot t\right) +\\
& a_7\cdot\sin\left(\frac{2\pi}{24}\cdot 7\cdot t\right) + b_7\cdot\cos\left(\frac{2\pi}{24}\cdot 7\cdot t\right) +\\
& a_8\cdot\sin\left(\frac{2\pi}{24}\cdot 8\cdot t\right) + b_8\cdot\cos\left(\frac{2\pi}{24}\cdot 8\cdot t\right) +\\
& a_9\cdot\sin\left(\frac{2\pi}{24}\cdot 9\cdot t\right) + b_9\cdot\cos\left(\frac{2\pi}{24}\cdot 9\cdot t\right) +\\
& a_{10}\cdot\sin\left(\frac{2\pi}{24}\cdot 10\cdot t\right) + b_{10}\cdot\cos\left(\frac{2\pi}{24}\cdot 10\cdot t\right) +
\end{aligned}$$

$$a_{11} \cdot \sin\left(\frac{2\pi}{24} \cdot 11 \cdot t\right) + b_{11} \cdot \cos\left(\frac{2\pi}{24} \cdot 11 \cdot t\right) +$$
$$a_{12} \cdot \sin\left(\frac{2\pi}{24} \cdot 12 \cdot t\right) + b_{12} \cdot \cos\left(\frac{2\pi}{24} \cdot 12 \cdot t\right).$$

2.3. The Application of the Immune System in Harmonic Analysis

A harmonic function can be expressed as follows:

$$y_t = a_0 + a_1 \cdot t + \sum_{i=1}^{m} \left(a_{2i} \cdot \sin\left(\frac{2 \cdot \pi \cdot i}{n} \cdot t\right) + a_{2i+1} \cdot \cos\left(\frac{2 \cdot \pi \cdot i}{n} \cdot t\right) \right), \quad (7)$$

where: a_i – coefficient, $i = 0, 1, 2, ..., 2 \cdot m$; n – the number of the month; i – the number of harmonic; t – the number of the time period; m – the number of the elements of time series.

In the presented method, coefficients a_i, $i = 0, 1, 2, ..., 2 \cdot m$ in the harmonic function will be matched using artificial immune algorithms (AIS).

Artificial immune systems are based on immunology principles (Wierzchoń 2001). The natural immune system uses certain protective barriers – skin, temperature or other conditions of a negative environment for antigens (Gołąb *et al.* 2010). The immune system reacts to the attacks of antigens in live systems, recognises pathogens, eliminates them and distinguishes between pathogens and its own cells that provoke the immune answer of the body. The system can also remember attacking antigens, which allows for the rapid mobilisation of the immune system when re-attacked.

Each lymphocyte can recognise one kind of the antigen. The lymphocytes that recognise attacking antigens are activated to proliferate rapidly. They produce a great number of clones. This process is called 'clonal selection' and is presented in Fig. 2.

Clones can mutate during the process of clonal selection. The new antibodies can recognise antigens better than their parent cells. After the process, the lymphocytes that remain in the system are converted into plasma or memory cells. The suppression mechanism prevents the over-stimulation of antibodies. The principle of clonal selection has its artificial implementation and is used for solving optimisation problems (De Castro, Von Zuben 1999).

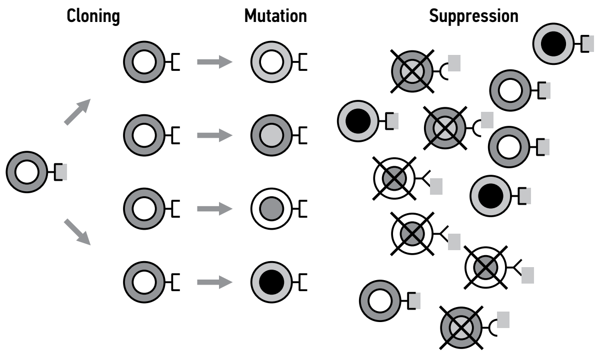

Fig. 2. The process of clonal selection

Coefficients a_i, $i = 0, 1, 2, ..., 2 \cdot m$ in the harmonic function (7) are represented as a vector of real numbers:

$$\{a_0, a_1, ..., a_n\}, \quad (8)$$

where: n – the number of coefficients in the function (7).

The coefficients (7) are optimisation variables. The vector (8) is the antibody in the considered model.

The measure of matching antibodies to the antigen is a fitness function:

$$F = \text{MAPE}^{-1}, \quad (9)$$

where MAPE (Mean Absolute Percentage Error) is defined as:

$$\text{MAPE} = \frac{1}{n} \cdot \sum_{t=1}^{n} \frac{\left| y_t - y_t^* \right|}{y_t} \cdot 100\%, \quad (10)$$

where: n – the number of observations; y_t – the value of time series for a moment or period of time t; y_t^* – the predicted value of y for a moment or period of time t; t – the number of the time period.

In the numerical model, only some data were used for determining the coefficients in the function (7). To take into account the changing trend, a part of them was used for determining the value of the fitness function, specifically in calculating the MAPE error.

When dealing with this problem, the coefficients of the harmonic analysis function in the formula (7) were calculated for the first 12 periods of time. The error (10) was calculated for $n = 24$ and y_t^* , $t = 1, ..., 24$.

The steps of artificial clonal selection are presented in Fig. 3.

Initiation. The vector (8) is randomised first. Each gene a_i is a real number sampled from the assumed range. The fitness function is calculated for every chromosome.

Cloning. Better antibodies are rapidly cloned. The number of clones was proportional to:

$$\frac{F}{\sum_{i=1}^{n} F_i}, \quad (11)$$

where: F – the fitness value of the considered antibody; $\sum_{i=1}^{n} F_i$ – the sum of fitness values for all population, n – population size.

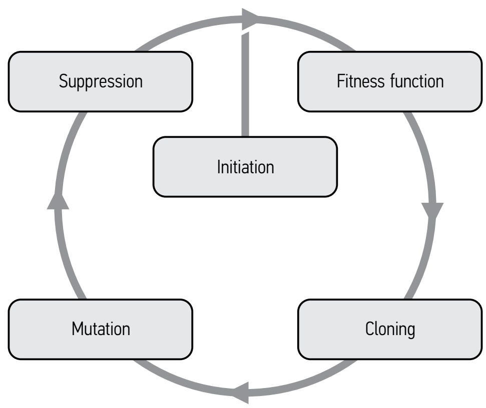

Fig. 3. The steps of artificial clonal selection

Mutation. Mutation operators change randomly the values of coefficients in (7). Changed antibodies can better recognise the antigen.

Suppression. A suppression mechanism controls the number of antibodies in the system. The worst cells are removed from the system. The other part is replaced by sampling. All procedures are stopped after the determined time of calculation elapsed or when MAPE error becomes small enough.

The best results of calculating the coefficients of the formula (7) were found and presented in Table 1.

The best results of forecasting freight volume calculations were found and presented in Table 2, the values are calculated in thousands of tons.

Table 1. The coefficients of harmonic analysis obtained using artificial immune algorithms

i	a_i	i	a_i
0	5500.4	12	–107903.0
1	171939.2	13	8298.9
2	21184.34	14	203030.3
3	212126.1	15	–163253.0
4	120186.1	16	57734.01
5	–56825.6	17	162869.4
6	–70815.6	18	–22066.0
7	–51113.1	19	54103.89
8	59797.7	20	107630.6
9	–16865.0	21	64324.7
10	205421.2	22	25024.09
11	164645.7	23	–213034.0

Table 2. Forecasting results given applying the artificial immune system in harmonic analysis

Forecasting volume [in thousand tons]			
1	136977.13	15	280162.89
2	191324.02	16	255654.57
3	214157.73	17	203647.73
4	189649.41	18	277484.26
5	137642.56	19	338918.02
6	211479.09	20	306620,38
7	272912.85	21	218564.12
8	240615.21	22	293952.05
9	152559.95	23	331613.18
10	227946.88	24	317437.54
11	265608.02	25	268987.46
12	251432.38	26	323334.35
13	202982.29	27	346168.05
14	257329.18		

3. Comparison of Researched Results

To compare different forecasting methods, the most common forecast errors were selected:

- RMSE (Root Mean Square Error):

$$\text{RMSE} = \sqrt{\frac{1}{n} \cdot \sum_{t=1}^{n} \left(y_t - y_t^* \right)^2}, \tag{12}$$

where: n – the number of observations; y_t – the value of time series for a moment or period of time t; y_t^* – the predicted value of y for a moment or period of time t, t – the number of the time period;

- Mean Absolute Percentage Error (MAPE) – formula (10).

Table 3 presents RMSE error in thousand tons and MAPE error in percentages [%] for three selected forecasting methods.

Table 4 presents the real value of road transport and the predicted value with three selected methods (value in thousand tons). Fig. 4 shows a graphical representation of the forecasting results.

Table 3. Comparison between selected forecasting methods

Selected methods / Comparative parameters	Winter's model: Multiplicative version	Harmonic analysis	Immune system
RMSE [thousand tons]	93624.78	90403.40	19193.78
MAPE [%]	8.33	8.09	4.14

Table 4. Comparison between the real and predicted value of road transport in Poland

Quarters[Q]	The actual value in 2010 in thousand tons	Predicted value in 2010 in thousand tons in different methods and formula		
		Winter's method (1)	Harmonic analysis (6)	Immune system (7)
Q1	220691.00	232187.00	303395.48	268987.50
Q2	335294.00	301751.19	334521.84	323334.30
Q3	361214.00	341316.84	323076.85	346168.10

4. Conclusions

1. The paper discusses traditional forecasting methods and those based on artificial intelligence.
2. The chosen methods of prediction include
   - seasonal Winter's method,
   - harmonic analysis,
   - harmonic analysis aided by the artificial immune system used for forecasting road freight volume in Poland for the period 2009–2010; a graphical presentation of forecasting results is shown in Fig. 4.
3. The most popular method used in economy is connected with the seasonal Winter's forecasting method and harmonic analysis.

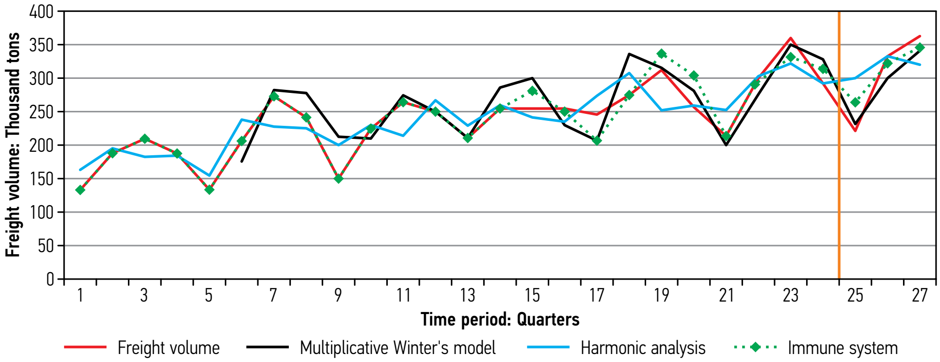

Fig. 4. Graphical presentation of forecasting results

4. The methodology of forecasting in the case of three chosen methods was presented. The main focus of research was put on the artificial immune system.
5. The Root Mean Square Error and Mean Absolute Percentage Error have been used for calculating and presenting effectiveness in the case of each selected method, thus comparing the results of prediction.
6. Due to the fact that the smallest error has been found in the artificial immune system and makes 4.14%, it can be stated that the most effective method of forecasting is the artificial immune system.
7. The major error reached 8.33% and was found in the seasonal Winter's method of forecasting. In harmonic analysis, MAPE was 8.09% and as a result, traditional methods were claimed to be the least accurate to predict economic phenomena and issues.

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