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Karolina ŁACHACZ, Bogna MRÓWCZYŃSKA, Tomasz HANISZEWSKI

ANALIZA PORÓWNAWCZA REZULTATÓW PROGNOZOWANIA WIELKOŚCI PRZEWOZÓW TOWAROWYCH W POLSCE W 2010 ROKU WTBRANYMI METODAMI PREDYKCJI

Streszczenie. W artykule skupiono się na analizie metod prognostycznych, które mogą zostać użyte do predykcji wielkości przewozów transportowych. W szczególności zwrócono uwagę na zagadnienie prognozowania z perspektywy ich różnorodności. Przedstawiono cztery metody prognozowania i zbadano ich efektywność. Rezultaty przeprowadzonych badań zostały omówione i porównane między sobą. Wybrano najlepszą metodę prognozowania.

COMPARATIVE ANALYSIS OF FORECASTING RESULTS FOR THE ROAD FREIGHT VOLUME IN POLAND IN 2010 WITH CHOSEN PREDICTION METHOD

Summary. The paper is focused on the analysis of forecasting methods that can be used in forecasting the volume of road freight. Draws attention to the issue of forecasting from the perspective of methods diversity. In the article four methods of prediction were selected, their effectiveness was researched. The results of various calculations were discussed and compared with each other. The best method of forecasting was presented.

1. METHODS OF FORECASTING – LITERATURE ANALYSIS

Forecasting is the rational, scientific prediction of future events [1]. Scientific prediction means that the whole process of forecasting, including:

- data collection,
- diagnosis,
- transferring data from the past into the future,
- formulation of objectives,
- conclusions, the achievements of science is used.

The object of forecasting is mostly a social, economic or production system, etc.. In this object there is a forecast phenomenon which is described by a number of variables (one or many variables). The main purpose of economic forecasting is to assist decision-making processes. These decisions may be of strategic, tactical or operational [2].

More and more often in production work is based on Just In Time system, and even Just in Sequence therefore, transport companies must adjust their activities to the requirements of the manufacturer. Determining the size and quantity of the transport needs would not be possible without an adequate forecasting based on sales volume or the demand for this service from past periods.

Currently, to the most commonly applied forecasting methods, used in determining the size of future demand, sales, transportation needs, can be included time series data methods. These methods includes trend analysis, seasonal or cyclical changes (Winters model, harmonic analysis etc.). Much more smaller share in forecasting methods based on artificial intelligence has had. However, the next step towards a more accurate prediction will be to use of artificial intelligence methods such as:

- genetic, immune, ant algorithm,
- or neural network.

Forecasting is not a simple process. Implementation of forecasting for the company, is a multi-stage operation. This process also requires many assumptions, which will allow proper selection of a predictive model compatible with the needs of the enterprise. Poorly chosen method of forecasting can cause many problems that result in financial consequences. In the case of individual companies it may be associated with an insufficient amount of materials, transport base, or the opposite - the frozen capital [3].

In forecasting demand, there are two basic approaches to prediction: quantitative and qualitative [7]. Both the traditional methods and models based on artificial intelligence can support the forecasting process in both areas. The use of artificial intelligence systems, however, should support the growth of the accuracy of the results.

2. THE STUDY OF FREIGHT VOLUME WITH CHOSEN PROGNOSTIC METHODS

Forecasting methods based on static and econometrics analysis are well developed in scientific publications as well as in business practice [1, 7, 8, 9]. Companies in the scope of their duties usually applies methods like time series analysis (seasonal models like: Winters Holt methods, harmonic analysis, trend analysis like: linear etc.).

Modern methods of forecasting based on artificial intelligence has not found as much use as traditional methods in business practice. But there are many publications where artificial intelligence methods are characterized and which use artificial system in a variety of issues. These issue includes:

- Forecasting of demand [4],
- Forecasting of materials flow [5],
- Timetable planning [6],
- Manufacturing process planning [10],
- Optimization of distribution system [12].

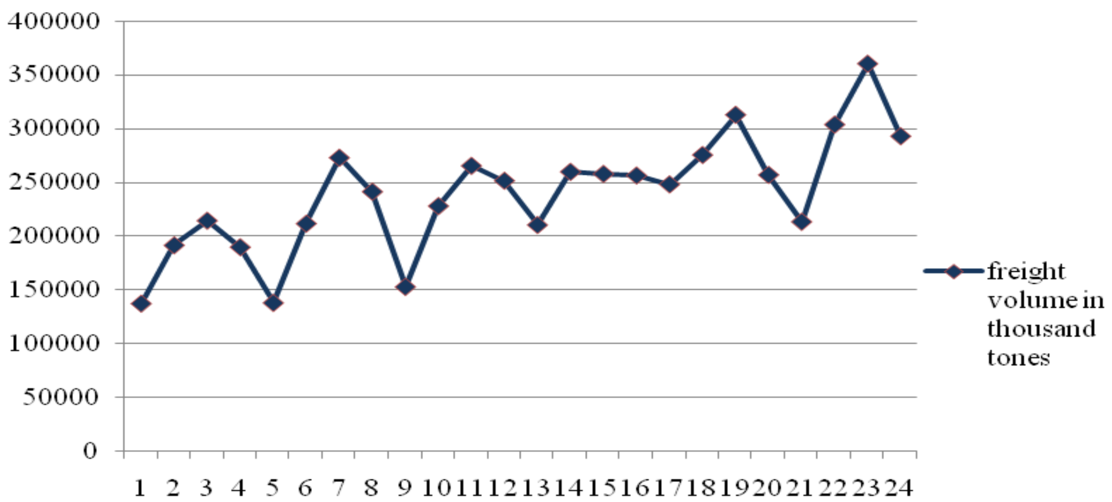
This article, however, is not a characteristics of the different artificial intelligence model and traditional techniques, because they are widely reported. The article presents the practical use of chosen forecasting models in predicting the volume of the road fright in Poland in 2010.

Calculations are based on data from the CSO regards to the volume of freight road transport in Poland in 2004-2009 [11]. Table 1 summarizes the data related to volume of road freight in thousands of tones [t] between 2004 and 2009.

Table 1

Freight volume in thousand tones for successive periods of time from 2004 to 2009

S. n.	Freight volume in thousand t	Quarter	Years	S. n.	Freight volume in thousand t	Quarter	Years
1	136965	1	**2004**	**13**	210232	1	**2007**
2	191306	2		**14**	259801	2	
3	214226	3		**15**	257823	3	
4	189552	4		**16**	256382	4	
5	137605	1	**2005**	**17**	248087	1	**2008**
6	211544	2		**18**	275484	2	
7	272931	3		**19**	312900	3	
8	241316	4		**20**	256934	4	
9	152571	1	**2006**	**21**	213214	1	**2009**
10	227915	2		**22**	303790	2	
11	265433	3		**23**	360530	3	
12	251495	4		**24**	292944	4	



Rys. 1. Graphical representation of data in the table (freight volume in thousand tones) [11]
Fig. 1. Graphical representation of data in the table (freight volume in thousand tones) [11]

Based on the data analysis the occurrence of seasonality in the volume of freight in each analyzed years with upward trend were founded. For the time series analysis with seasonal fluctuations the several forecasting methods were used:

– Winter's seasonal model,
– Harmonic analysis,
– Genetic algorithm.

The aim of the study is to compare the forecasting results formulated on chosen methods and selection of the one which has the highest accuracy. The effectiveness measure will be calculated by forecast error.

2.1. Seasonal Winter's method

Formulas which are used to forecasting in the Winter's model were presented in table 2 [1].

Table 2

Forecasts for future periods in the Winter's model

	Additive model	Multiplicative model
Forecast for future periods	a) $y_t^* = F_n + S_n(t-n) + C_{t-r}$ b) $y_t^* = F_{t-1} + S_{t-1} + C_{t-1}$	a) $y_t^* = \left(F_n + (t-n)\cdot S_n\right)C_{t-r}$ b) $y_t^* = (F_{t-1} + S_{t-1})C_{t-r}$
Smoothed evaluation of the average value level for the time period t	$F_{t-1} = \alpha(y_{t-1} - C_{t-1-r}) + (1-\alpha)(F_{t-2} + S_{t-2})$	$F_{t-1} = \alpha \dfrac{y_{t-1}}{C_{t-1-r}} + (1-\alpha)(F_{t-2} + S_{t-2})$
Smoothed value of trend growth for the time period t:	$S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1-\beta)S_{t-2}$	$S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1-\beta)S_{t-2}$
The evaluation of seasonality index for time period t:	$C_{t-1} = \gamma(y_{t-1} - F_{t-1}) + (1-\gamma)C_{t-1-r}$	$C_{t-1} = \gamma \dfrac{y_{t-1}}{F_{t-1}} + (1-\gamma)C_{t-1-r}$

Źródło: [1]

where: t – number of time period; n – number of observation; a) – t>n; b) –t<n; r – period; y_t – the torque of predicted value for the time period t; α - smoothing parameter of level predicted variable with values from the interval (0,1); β – smoothing parameter which is related to growth due to trend of the values in the interval of (0,1); γ – evaluation parameter of the seasonality index with values from the interval of (0,1); r – seasonal cycle length (number of phases of each cycle).

The best α; β, γ parameters were selected with using solver in each model, which were presented in table 3.

Table 3

The best α; β, γ parameters in multiplicative and additive model

Parameter	Multiplicative model	Additive model
α	1,00	1,00
β	0,20	0,15
γ	0,25	0

2.2. Harmonic analysis

In case of time series analysis its enable to use harmonic analysis in forecasting. This issue will be written as sum of individual harmonics [18]:

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

where: f(t) – trend function; n – number of month; i – number of harmonic; t – number of time period.

In harmonic analysis the function parameters may be estimated with ordinary least squares method (OLSM). What is more, amplitudes, the percentage of endogenous variation, the size of phases and phase shift must be calculated too. In case of freight volume forecasting the number of harmonic is equal to n/2 = 12. Estimated line trend function:

$$\hat{y}_t = a + b \cdot t = 167143{,}18 + 5765{,}15 \cdot t, \tag{2}$$

Estimated model of harmonic analysis is defined as:

$$\begin{aligned}
\hat{y}_t &= 167143{,}18 + 5765{,}15 \cdot t \\
&+ a_1 \cdot \sin\left(\frac{2\pi}{24} \cdot t\right) + b_1 \cdot \cos\left(\frac{2\pi}{24} \cdot t\right) + a_2 \cdot \sin\left(\frac{2\pi}{24} \cdot 2 \cdot t\right) + b_2 \cdot \cos\left(\frac{2\pi}{24} \cdot 2 \cdot t\right) \\
&+ a_3 \cdot \sin\left(\frac{2\pi}{24} \cdot 3 \cdot t\right) + b_3 \cdot \cos\left(\frac{2\pi}{24} \cdot 3 \cdot t\right) + a_4 \cdot \sin\left(\frac{2\pi}{24} \cdot 4 \cdot t\right) + b_4 \cdot \cos\left(\frac{2\pi}{24} \cdot 4 \cdot t\right) \\
&+ a_5 \cdot \sin\left(\frac{2\pi}{24} \cdot 5 \cdot t\right) + b_5 \cdot \cos\left(\frac{2\pi}{24} \cdot 5 \cdot t\right) + a_6 \cdot \sin\left(\frac{2\pi}{24} \cdot 6 \cdot t\right) + b_6 \cdot \cos\left(\frac{2\pi}{24} \cdot 6 \cdot t\right) \\
&+ a_7 \cdot \sin\left(\frac{2\pi}{24} \cdot 7 \cdot t\right) + b_7 \cdot \cos\left(\frac{2\pi}{24} \cdot 7 \cdot t\right) + a_8 \cdot \sin\left(\frac{2\pi}{24} \cdot 8 \cdot t\right) + b_8 \cdot \cos\left(\frac{2\pi}{24} \cdot 8 \cdot t\right) \\
&+ a_9 \cdot \sin\left(\frac{2\pi}{24} \cdot 9 \cdot t\right) + b_9 \cdot \cos\left(\frac{2\pi}{24} \cdot 9 \cdot t\right) + a_{10} \cdot \sin\left(\frac{2\pi}{24} \cdot 10 \cdot t\right) + b_{10} \cdot \cos\left(\frac{2\pi}{24} \cdot 10 \cdot t\right) \\
&+ a_{11} \cdot \sin\left(\frac{2\pi}{24} \cdot 11 \cdot t\right) + b_{11} \cdot \cos\left(\frac{2\pi}{24} \cdot 11 \cdot t\right) + a_{12} \cdot \sin\left(\frac{2\pi}{24} \cdot 12 \cdot t\right) + b_{12} \cdot \cos\left(\frac{2\pi}{24} \cdot 12 \cdot t\right)
\end{aligned}$$

2.3. Genetic algorithm model

Genetic algorithm model for harmonic analysis can also be expressed as:

$$y_t = a_0 + a_1 t + \sum_{i=1}^{m} [a_{2i} \sin(\frac{2\pi i}{n} t) + a_{2i+1} \cos(\frac{2\pi i}{n} t)], \tag{3}$$

The coefficients a_i, i = 0, 1, 2, ..., 2m in harmonic function can also be matched with using artificial genetic algorithms (GA). GA are the methods of artificial intelligence and simulate the evolutionary process [14]. Problem which is solving, is represented by a chromosomes. The genes in the chromosomes are the variables in solving problems. The population of chromosomes is subjected to genetic operations in each generation. Pairs of chromosomes are crossed over and individual chromosomes are subjected to mutation with the specified probabilities. Each chromosome is evaluated, assigned to the fitness function. All chromosomes are subjected to selection. The best move to the next generation.

Table 4 presents the coefficients of the harmonic analysis (3) obtained using artificial genetic algorithms.

Table 4

Freight The coefficients of the harmonic analysis obtained using artificial genetic algorithms

i	a_i	i	a_i	i	a_i	i	a_i	i	a_i
0	3538,93	6	-4646,61	12	-44207,39	18	1709,09	24	1150252,35
1	194506,72	7	7847,27	13	-1934,3	19	408,94	25	6090,06
2	-12083,41	8	-627,7	14	-1626,03	20	6,03		
3	-1431,58	9	12802,03	15	3767,55	21	3599,51		
4	-7002,76	10	-10394,12	16	-756,26	22	-3803,50		
5	2023,22	11	-9235,43	17	-8593,82	23	-1913,49		

In the presented calculations the chromosomes are sets of coefficients $\{a_i: i = 0, 1, ..., 25\}$ from equation (3), which are the real numbers matched from pre-defined intervals. The best results of the calculations presented in table 5.

Table 5

Results of forecasting which are given from artificial genetic algorithm

S. n.	Freight volume in thousand t	Forecasting volume	S. n.	Freight volume in thousand t	Forecasting volume
1	136965	135474,06	**13**	210232	210977,53
2	191306	185413,42	**14**	259801	258827,06
3	214226	212755,52	**15**	257823	233010,64
4	189552	175522,56	**16**	256382	254404,97
5	137605	133746,71	**17**	248087	229732,10
6	211544	211980,01	**18**	275484	277657,97
7	272931	273867,52	**19**	312900	331218,30
8	241316	234449,35	**20**	256934	261017,55
9	152571	148516,69	**21**	213214	209290,81
10	227915	224095,05	**22**	303790	299832,04
11	265433	255630,35	**23**	360530	366482,69
12	251495	248451,33	**24**	292944	387392,32
EX POST ERRORS					
MAPE		0,17	**RMSE**		2519,71

3. RESEARCH RESULTS COMPARISON

To compare different forecasting methods, the most common forecast errors were selected [18]:

– RMSE (Root Mean Square Error):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - y_t^*)^2}\ , \tag{4}$$

– MAPE (Mean Absolute Percentage Error), the average absolute percentage error:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|y_t - y_t^*\right|}{y_t}\cdot 100\%\ , \tag{5}$$

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

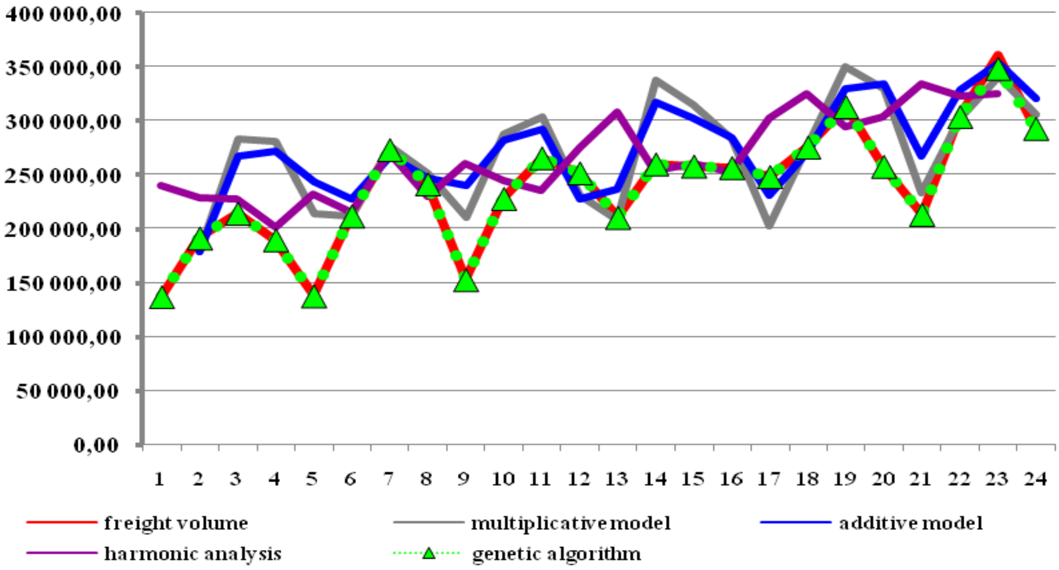
Table 6 presents comparison between selected forecasting methods.

Table 6

Comparison between selected forecasting methods

Seleted methods / **Comparative parameters**	**Seasonal Winters model**		**Harmonic analysis**	**Genetic algorithm**
	Multiplicative model	**Additive model**		
RMSE	98 956,64	100 462,55	94067,76	2519,71
MAPE	8,51	8,91	7,91	0,17

Fig. 2 shows graphical presentation of forecast results.



Rys. 2. Forecast results for chosen prediction methods.
Fig. 2. Forecast results for chosen prediction methods.

4. CONCLUSION

In the paper the chosen forecasting methods were used. The most popular is connected with multiplicative and additive model of seasonal Winters forecasting method and harmonic analysis. Artificial intelligence [AI] methods were used to forecasting freight volume in scientific research. An article presents effectiveness in each case and compares results of prediction. The results of calculation was discussed. The best method of forecasting was presented. The smallest error was 0,17% and it was found in genetic algorithm and the highest 8,91% and found in additive model. As the best method has been recognized the genetic algorithm, as the worst seasonal winters method additive model.

Bibliography

1. Ditmann P.: Prognozowanie w przedsiębiorstwie. Metody i ich zastosowanie. Wolters Kluver Polska – Oficyna, Kraków 2008.
2. Chodak G., Kwaśnicki W.: Zastosowanie algorytmów genetycznych w prognozowaniu popytu. Gospodarka Materiałowa i Logistyka, nr 4, 2002, s. 2-7.
3. Góralczyk A.: Zamrożony kapitał. CEO – Magazyn Top Menadżerów, nr 06/2004, http://ceo.cxo.pl/artykuly/42038/Zamrozony.kapital.html.
4. Chodak G.: Genetic algorithms in forecasting of internet shops demand, [in:] Świątek J. at al. (eds.): Information systems architecture and technology: system analysis in decision aided problems. Oficyna Wydawnicza Politechniki Wrocławskiej, Wrocław 2009, s. 59-68.
5. Ludwig O. Jr., Nunes U., Araújo R., Schnitman L., Lepikson H.A.: Applications of information theory, genetic algorithms, and neural models to predict oil flow. Communication in Nonlinear Science Numerical Simulation, No. 14, 2009, p. 2870-2885.
6. Bhaduri A.: University time table scheduling using genetic artificial immune network, advances in recent technologies in communication and computing, ARTCom '09. International Conference on, Kottayam, Kerala 2009, p. 289-292.
7. Nowak E. (red.): Prognozowanie gospodarcze – metody, modele, zastosowania, przykłady. Agencja Wydawnicza PLACET, Warszawa 1998.
8. Jóźwiak J., Podgórski J.: Statystyka od podstaw. PWE, Warszawa 2009.
9. Larose D.T.: Metody i modele eksploracji danych. PWN, Warszawa 2008.
10. Jung H., Song I., Jeon B.: Genetic algorithm-based integrated production planning considering manufacturing partners. International Journal Advanced Manufacturing Technology, No. 3, 2007, p. 547-566.
11. GUS: dane kwartalne wskaźników gospodarczych, http://www.stat.gov.pl/gus/wskazniki_makroekon_PLK_HTML.htm.
12. Hua Z., Ding Y., Shao Q.: Immune co-evolutionary algorithm based partition balancing optimization for tobacco distribution system. Expert Systems with Applications, no. 36, 2009, p. 5248-5255.
13. Zeliaś A., Pawełek B., Wanat S.: Prognozowanie ekonomiczne: teoria, przykłady, zadania. PWN, Warszawa 2004.
14. Michalewicz Z.: Genetic algorithms + data structures = evolutionary programs. Springer-Verlag, Berlin 1996.

Recenzent: Dr hab. Maria Michałkowska, prof. nzw. Uniwersytetu Ekonomicznego
w Katowicach