Artificial Intelligence Methods in Spare Parts Demand Forecasting

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The paper discusses the problem of forecasting lumpy demand which is typical for spare parts. Several prediction methods are presented in the article – traditional techniques based on time series and advanced methods that use Artificial Intelligence tools. The research conducted in the paper focuses on comparison of eight forecasting methods, including classical, hybrid and based on artificial neural networks. The aim of the paper is to assess the efficiency of lumpy demand forecasting methods that apply AI tools. The assessment is conducted by a comparison with traditional methods and it is based on Root Mean Square Errors (RMSE) and relative forecast errors (*ex post*) values. The article presents also a new approach to the lumpy demand forecasting issue – a method which combines regression modelling, information criteria and artificial neural networks.

Keywords: lumpy demand, forecasting, ANN, Artificial Intelligence.

1. INTRODUCTION

The relevance of spare parts management cannot be overemphasized. It remains the most neglected area of management[1]. Distressing issue of repeated breakdowns leading to low capacity utilization in many sectors brings to focus urgent need for formulating a well-organized spare parts management policy in various organizations. An important part of such a policy is spare parts demand forecasting. Spare parts management is an issue of large uncertainty and it is characterized by fluctuations in demand[2].

P. Gopalakrishnan and A. K. Banerji surveyed many enterprises to conduct research on spare parts management[3]. When it comes to financial aspects, their research show that 2-5% of the total project cost is usually invested in the spares inventory at the moment of starting the project. About 10% of the cost of an equipment is invested in the recommended spare parts at the time of procurement of the factory. Many of these spares are found to be non-moving or obsolete later on. About 40% of the working capital of spares intensive process, mining and transport industries is tied in the spare parts inventories. 25% of them usually forms non-moving or obsolete items. The obsolescence rate is higher in technologically advanced industries. What is more, 60 to 80% of the maintenance expenditure is accounted by spare parts consumption in industries. The average spares consumption for the machineries varies from 1 to 3 % of the annual sales value of the output. Lack of capital in the enterprises often results in using the equipment for longer duration, sometimes to the extent of overworking the machinery beyond the operational or economic

[1] P. Gopalakrishnan, A. K. Banerji, Maintenance And Spare Parts Management, PHI Learning Pvt. Ltd., New Delhi, 2006, p. XV.

[2] M. Młyńczak, Problematyka prognozowania zużycia części wymiennych, Logistyka i Transport, Logistyka produkcji samochodów i części zamiennych, Scientific – Technical Conference, Wrocław, 18 – 19.12.2008, p. 66.

[3] P. Gopalakrishnan, A. K. Banerji, Maintenance And Spare Parts Management, PHI Learning Pvt. Ltd., New Delhi, 2006, p. 213-219.

life. Unfortunately this habit is quite popular in many companies.

Presented aspects clearly show that spare parts management, including spare parts demand forecasting, is an issue of great importance in many enterprises. In a company, the problem of spare parts management is the more urgent, the higher machines failure rate is. In this context the environment in which machines are operated is especially important, because it is often the most important factor influencing the failure rate. The environment of the exploitation system can be defined as all the external variable physical conditions among which a technical object operates[4]. While analyzing different sectors of economy, it can be noticed that especially companies from mining industry suffer from very high machines failure rate[5]. It is caused by very specific environment in which machines work. Machines, that are in almost constant motion, break down very often due to high temperatures, high level of humidity and poor state of routs.

If a company uses a demand forecasting method of poor quality when it comes to forecast accuracy or does not use any method at all, then certain wastes can be noticed due to lack of spare parts or due to excessive inventories. Wastes caused by lack of spares include repair time extension, disorganization of work, machine's unavailability and threat that the production plan will not be executed. It also generates shortage cost (often including stockout cost). On the other hand, excessive inventories are also considered as waste. In this case, excessive inventories cause space problems, generate storage costs (excess costs and holding costs), very often depreciation problem occurs.

Described issues clearly show how important is the usage of efficient demand forecasting methods. This is why the research presented in the paper focuses on comparison of eight forecasting methods, including classical, hybrid and based on artificial neural networks. The main aim of the article is to assess the efficiency of lumpy demand forecasting methods that use AI tools. The assessment is conducted by a comparison with traditional methods. The paper presents also a new approach to the lumpy demand forecasting issue – a method which combines regression modelling, information criteria and artificial neural networks.

2. FORECASTING METHODS

The issue of spare parts demand forecasting has been studied for many years, which has resulted in the development of numerous prediction methods and techniques[6]. A demand forecast can be defined as company's best estimate of what demand will be in the future, given a set of assumptions[7]. Forecasting techniques can be separated into two general categories – qualitative and quantitative – as shown in Table 1[8].

Table 1. Qualitative and quantitative forecasting methods

Qualitative Methods	**Quantitative Methods**	
	Time Series Methods	**Causal Methods**
Judgment	Moving Average, Weighted moving average	Regression
Historical Analogy	Exponential Smoothing	Econometric
Focus Group	Trend Analysis	Input-Output
Market Research	Decomposition	Disaggregated
Diffusion	Advanced Time Series methods	Neural Networks
Markovian	Box-Jenkins (ARIMA)	

Source: K. D. Lawrence, R. K. Klimberg, S. M. Lawrence, Fundamentals of Forecasting Using Excel, Industrial Press 2009

Qualitative prediction methods are commonly used when there is little or no data available. In

[4] T. Nowakowski, Metodyka prognozowania niezawodności obiektów mechanicznych, Oficyna Wydawnicza Politechniki Wrocławskiej, Wrocław, 1999, p. 45.

[5] R. Król, R. Zimroz, Ł. Stolarczyk, Analiza awaryjności układów hydraulicznych samojezdnych maszyn roboczych stosowanych w KGHM POLSKA MIEDŹ S.A., Prace Naukowe Instytutu Górnictwa Politechniki Wrocławskiej, **N°** 128, **N°** 36.

[6] P. Kozik, J. Sęp, Aircraft engine overhaul demand forecasting using ANN, Management and Production Engineering Review, Vol.3, Nr 2, June 2012, p. 21–22.

[7] M. A. Moon, Demand and Supply Integration: The Key to World-Class Demand Forecasting, FT Press, USA, 2013.

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general, these methods are less structured in comparison to quantitative techniques. A judgment forecasting method (eg. Delphi method) elicits management's opinions to provide a forecast. Historical analogy obtains information from experts who have faced similar situations in the past. Another method is a focus group. It involves an objective moderator who introduces a topic to a group of respondents, and directs their discussions in a non-structured and natural fashion. The focus group is a source of rich information that cannot be provided by a survey. However, a main disadvantage of this method is that the results obtained from a focus group cannot be generalized – the information is valid only for that homogeneous group. Diffusion models are implemented mainly to predict the fate of new products, while Markovian models to forecast consumers and buyers behaviours. Basic disadvantage of qualitative techniques is that forecasts are subjective, because they base on opinions that can be biased. Nevertheless these methods are quite popular due to their simplicity, understandability and relatively low costs.

The other group of forecasting methods are quantitative techniques. In general these methods use historical data to predict future values, so it is often necessary to gather a lot of data. Quantitative methods can be divided into two groups – time series methods and causal methods. Time series techniques base only on the time series data itself to build the forecasting models. So in case of predicting future values of spare parts demand, only data regarding past demand is required. Time series methods include Moving Average (MA) and Weighted Moving Average (WMA), Exponential Smoothing (Single Exponential Smoothing, SES) and Box-Jenkins method (e.g. ARIMA).

The other group of quantitative methods are causal methods. They use a set of explanatory variables, often including time series components, that are believed to influence the predicted value, like spare parts demand. These methods include econometrical prediction based on regression analysis and artificial neural networks (ANN).

Except from methods listed above, some other quantitative forecasting techniques have been developed. Method dedicated to spare parts demand forecasting are especially Croston's method (CR) and Syntetos-Boylan method (SBA). Methods used for demand prediction include also Additive/ Multiplicative Winters model, Binomial method, Grey's prediction model, Bootstrap and Poisson's method.

Classification of forecasting methods may be also based on the time period associated with the analyzed demand data[9]. The models used in short-time forecasting should be simple and relatively cheap. The group of models based on the exponentially weighted average, originally suggested by Holt, has proved to be more satisfactory than any other. It has become the basis for forecasting in many inventory control situation due to its computational cheapness, robustness, adaptability and flexibility. According to category of the forecast, certain forecasting techniques can be recommend. When considering immediate-term forecasts, applied eg. in electricity demand forecasting, various prediction methods may be used. For short-term forecasts (eg. demand in industry and commerce) exponentially weighted averages and derivatives are recommended. For medium-term forecasts (e.g. sales and financial forecasting) it is advisable to use regression, curve fitting or time series analysis. In case of long-term forecasts (applied in e.g. technological forecasting) methods like DELPHI or think tanks are recommended.

3. ARTIFICIAL INTELLIGENCE METHODS IN DEMAND FORECASTING

One of the most popular Artificial Intelligence (AI) method is ANN. There are many types of artificial neural networks. Basic classification groups ANN into those dedicated to classification problems ANN(class.)) and those dedicated to regression problems (ANN(regr.)). In classification problems, the purpose of the network is to assign each case to one of a number of classes. Nominal output variables are used to indicate a classification problem. The nominal values correspond to the various classes. Very often used technique is the one where there is only two-state variable. In that case a single node corresponds to the variable, and a value of 0 is interpreted as one state, and a value of 1 as the other. ANN dedicated to classification problems in spare parts demand forecasting are used so that value 0 means that the demand equals 0, and value 1 means that there is a non-zero value of demand (ANN(class.)). In regression problems (ANN(regr.)), the objective is to estimate the value

[9] C.D. Lewis, Demand Forecasting and Inventory Control: A Computer Aided Learning Approach, Woodhead Publishing Ltd, England, 1998, p. 6-7.

of a output variable, given the known input variables. A particularly important issue in regression is output scaling, and extrapolation effects.

Artificial neural networks are tool applied in many areas, including – sale forecasting, overhaul planning, machines diagnostics or production problems analysis[10]. The ANN application may be grouped in three categories – applications in speech (including NETtalk, phonetic typewriter, vowel classification, recognition of consonant-vowel (CV) segments, etc.), applications in image processing (including recognition of handwritten digits, image segmentation and texture classification and segmentation), applications in decision making[11]. There are several works where ANN where applied as a demand forecasting technique – including a neuro-based approach for Iran annual gasoline demand forecasting[12] or a dynamic artificial neural network model for comprehensive urban water demand forecasting[13].

Neural networks have been advocated as an alternative to traditional statistical forecasting methods. Classical methods, such as exponential smoothing or regression analysis, have been used for several decades in forecasting demand. However, many of these techniques may perform poorly when demand for an item is lumpy or intermittent. That kind of demand is characterized by intervals in which there is no demand and, for periods with actual demand occurrences, there is a large variation in demand levels[14]. Lumpy demand has been observed in heavy machinery spare parts, in the automotive industry, in durable goods spare parts and in aircraft maintenance service parts. In fact a little work has been done in lumpy demand forecasting using neural network. Some research was conducted by inter alia Carmo[15], Gutierrez[16], Nasiri Pour[17] and Kozik[18]. However the ANN application in spare parts forecasting demand still needs investigation. This is why this paper is dedicated to this problem. In order to develop possibility of using ANN in spare parts demand prediction and to compare its efficiency with traditional methods, the research was conducted. The results are presented in next chapter.

The research presented in this paper was conducted using data coming from a company in which machines were characterized by very high failure rate (low MTTF indicator (Mean Time To Failure), low MTTR indicator (Mean Time To Repair) and low MTBF indicator (Mean Time Between Failures).

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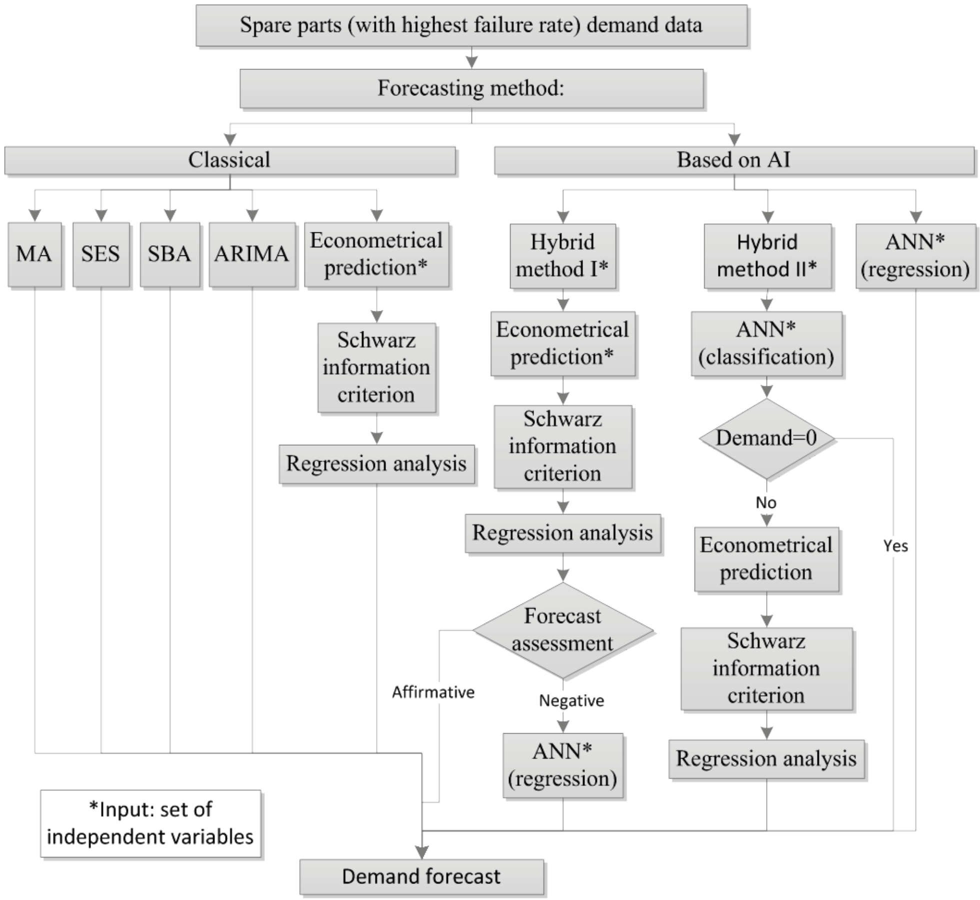

Fig. 1. Algorithm of calculations compering chosen forecasting methods

In order to find the best method appropriate for the company, several techniques were compared. An algorithm (Fig. 1) above presents the way the calculations comparing chosen methods were conducted. First step was to collect data regarding past demand for three types of spare parts with highest failure rate. Next, calculations were conducted using eight forecasting methods – five of them were classical methods (Moving Average MA, Simple Exponential Smoothing SES, Syntetos-Boylan method SBA, Autoregressive-integrated moving average ARIMA and econometrical prediction based on regression analysis). Methods dedicated to demand with seasonal trends (like e.g. Winters models) were not included due to the fact, that the spare parts demand in the company is independent from seasonal fluctuations. Three of eight forecasting methods base on AI. Two types of artificial neural networks were used – ANN dedicated to regression tasks and ANN dedicated to classification tasks. Two of three forecasting methods based on AI are hybrid methods. Basic steps of both techniques are presented at the figure above. When it comes to input data, it is important to notice, that econometrical prediction and methods using ANN use set of variables. Traditional methods mainly base on time series.

The first hybrid method (Hybrid method I) begins with econometrical prediction. At first stage a set of potential independent variables is determined. Then, in order to choose variables that significantly influence dependent variable (demand), an efficient method of model selection is used. One of the best methods is Schwarz's information criterion (called also Bayesian information criterion, BIC). Then, an econometrical model based on selected variables is built. Regression analysis based on least square method (LSM) is used to build the model. In next step, the model's ability to forecast properly is assessed. If the assessment is affirmative, the demand forecast is calculated. If not, then there is a need to use more advanced tool – artificial neural network. In this case, basing on the previously selected set of variables, an ANN is constructed (in the paper it is named ANN(BIC)). In the last step the demand forecast is computed.

The second hybrid method (Hybrid method II) bases on artificial neural network dedicated to classification tasks. This approach was presented by Nasiri Pour, Rostami Tabar, and A. Rahimzadeh[19]. Firstly it is necessary to convert demand time series to binary time series (0 – demand equals zero, 1 – there is nonzero demand). Then a set of independent variables is determined. Basing on that set, a neural network architecture is specified. A multi layered perceptron (MLP) neural network has been used for forecasting occurrence of demand. After building the ANN (in the paper it is named ANN(class.)), a forecast can be computed. If result coming from the ANN equals zero, it means that the predicted quantity of demand equals zero. However, if result coming from the ANN equals one, it means that the quantity of the demand is nonzero and its value needs to be calculated. Authors of this method recommend to compute quantity of demand using conventional method. In order to find the best classical technique to use with ANN, first of all, ability of all traditional methods in lumpy demand forecasting to compound with NN models was considered. Croston's method and combinations of this method (like e.g. SBA) could not be used, because in these methods it is necessary to forecast size and interval between demands for all periods, whereas in hybrid approach only quantity of nonzero periods needs to be predicted. This is why econometrical prediction was chosen. Next steps regarding usage of econometrical prediction are similar to those in Hybrid method I. In the last stage the demand forecast is calculated.

The last of three methods basing on AI is artificial neural network dedicated to regression tasks (in the paper it is named ANN(regr.)). As it was mentioned, all three methods that use ANN and econometrical prediction itself need a set of independent variables. In this paper, following variables were defined as an input:

- x_1 – number of days between two last demands in the time immediately preceding target period,
- x_2 – number of days between the target period and first nonzero demand immediately preceding target period,
- x_3 – number of days between the target period and first zero demand immediately preceding target period,
- x_4 – mean demand for six days immediately preceding target period,
- x_5 – maximum demand for six days immediately preceding target period,
- x_6 – total demand in the last week immediately preceding target period,
- x_7 – number of days in the week immediately preceding target period when there was nonzero demand,
- x_8 – number of days in the week immediately preceding target period when there was no demand,
- x_9 – mean demand for two weeks immediately preceding target period,
- x_{10} – time trend.

4. ANALYSIS OF EMPIRICAL DATA

To find the most appropriate demand forecasting method, data regarding three types of spare parts (each from different machines' module) were collected. These parts can be named as SP1, SP2 and SP3. Each type of the part breaks down very often. It causes a lot of problems in spare parts management issue. Frequent failures involve necessity of frequent repairs. In order to ensure right level of stock of given spare part, it is very important to calculate proper demand forecast. The better the forecast, the chance that the inventory level is accurate is bigger. Only application of efficient spare parts demand forecasting method may guarantee seamless repair.

The research was conducted according to the scheme presented in the previous chapter. Results from the artificial neural networks are presented in the following tables. Confusion matrix (Tab. 2) contains outcome from the ANN dedicated to classification tasks.

Table 2. Confusion matrix (ANN – classification)

Confusion matrix	**SP1**	**SP2**	**SP3**
	MLP 10-7-2	MLP 10-9-2	MLP 10-4-2
0 correct	620	1596	776
1 correct	108	145	259
0 wrong	0	0	0
1 wrong	0	0	0

As it can be noticed, for all three spare parts types there is 100% efficiency in classification

[19] A. Nasiri Pour, B. Rostami Tabar, A. Rahimzadeh, A Hybrid Neural Network and Traditional Approach for Forecasting Lumpy Demand, World Academy of Science, Engineering and Technology 40 2008.

(due to very big sample size). For SP1 there were 728 daily periods analyzed (from 1.04.2011 to 31.12.2012), for SP2 1741 periods (from 7.03.2008 to 11.12.2012) and for SP3 1035 periods (from 3.03.2010 to 31.12.2012). For SP1 – 108 out of 728 times the demand was nonzero and 620 it was equal zero. Result for SP2 and SP3 can be found in the table. All the networks consists of three layers. First network (for SP1) is built from ten neurons in the input layer, seven neurons in the hidden layer and two neurons in the output layer. Second NN (for SP2) is constructed on the basis of ten neurons in the input layer, nine neurons in the hidden layer and two neurons in the output layer. Third NN (for SP3) also has ten neurons in the input layer and two neurons in the output layer, but the hidden layer consists of only four neurons.

Next table (Tab. 3) contains outcomes from ANN built according to Hybrid method I and ANN dedicated to regression problems (Third method out of those based on AI).

six neurons in the hidden layer and one neuron in the output layer. In the last network (SP3) there are four neurons in the input layer, nine neurons in the hidden layer and one neuron in the output layer.

Next figure (Fig. 2) presents Root Mean Square Errors (RMSE) calculated for all eight analyzed methods. Root Mean Square Error is a measure of the differences between values predicted by a model and the values actually observed. RMSE is quite good measure of accuracy to compare forecasting errors of different methods. As it is scale-dependent its values for three different spare parts cannot be compared. Almost all classical methods (MA, SES, SBA, ARIMA) are characterized by very high RMSE – for each analyzed spare part. Only economical prediction (regression model) presents lower RMSE in comparison to other traditional methods. Comparable to economical prediction is Hybrid method II (Hybrid II ANN (class.)). Values of

Table 3. ANN (regression) and ANN (BIC) results

SP1	Network	Quality (training)	Quality (testing)	Quality (validation)
ANN (regression)	MLP 10-7-1	0,942	0,966	0,946
ANN (BIC)	MLP 3-9-1	0,954	0,970	0,975
SP2				
ANN (regression)	MLP 10-4-1	0,914	0,888	0,856
ANN (BIC)	MLP 4-6-1	0,932	0,903	0,936
SP3				
ANN (regression)	MLP 10-4-1	0,917	0,987	0,993
ANN (BIC)	MLP 4-9-1	0,918	0,989	0,994

All the networks give very good results. Quality for training, testing and validation sets exceeds 90% in most cases. Network dedicated to regression tasks for SP1 is built from ten neurons in the input layer, seven neurons in the hidden layer and one neuron in the output layer. Similar structure have two other ANN of this type. For SP2 and SP3 there are four neurons in the hidden layer. Networks constructed according to the Hybrid method I are built on variable set selected by the BIC criterion. There are three neurons in the input layer, nine neurons in the hidden layer and one neuron in the output layer for the SP1 ANN (BIC). For SP2 there are four neurons in the input layer,

RMSE are similar. The best results can be noticed when it comes to other two methods based on AI. Hybrid method I (Hybrid I ANN (BIC)) and artificial neural network dedicated to regression tasks (ANN (regr.)) are characterized by low RMSE. For SP1 RMSE equals 0,032 for Hybrid I ANN (BIC) and 0,070 in case of ANN (regr.). Similar results can be noticed for parts SP2 and SP3. For SP2 RMSE equals 1,232 for Hybrid I ANN (BIC) and 1,240 for ANN (regr.). In case of SP3, RMSE of Hybrid I ANN (BIC) method amounts 2,658 and RMSE of ANN (regr.) method amounts 3,014. These results show that the lowest values of RMSE characterize methods based on

AI, especially Hybrid method I and artificial neural networks dedicated to regression.

Relative forecast errors are quite similar in case of artificial neural networks dedicated to regression

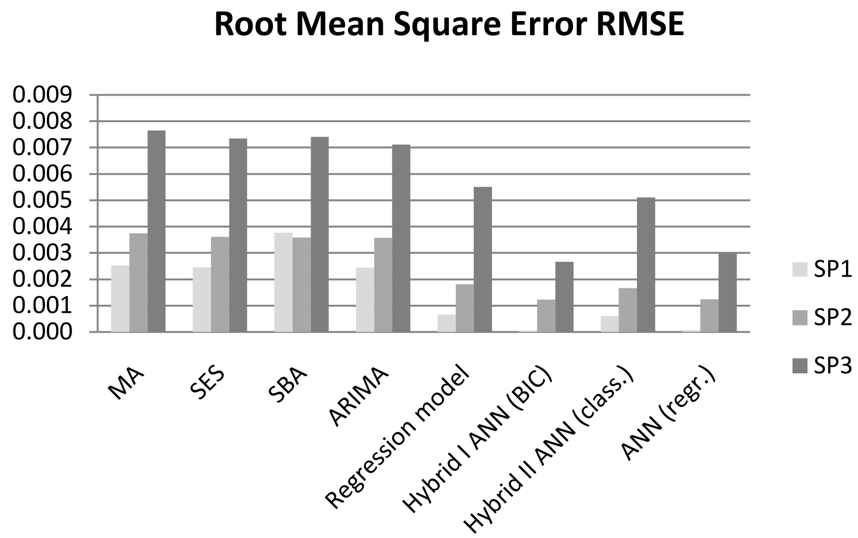

Fig. 2. Root Mean Square Error

Next figure (Fig. 3) presents values of relative forecast error (*ex post*) computed for eight methods. This measure of goodness of forecasting is scale-independent. Again, almost all classical methods are characterized by high relative forecast error. Economical prediction and Hybrid method II for all three parts present better results in comparison to traditional methods, but they are less effective than Hybrid method I and artificial neural networks dedicated to regression tasks. Values of relative forecast error (*ex post*) are the lowest for Hybrid method I (Hybrid I ANN (BIC)).

tasks. For SP1 relative forecast errors does not exceed 3% in case of Hybrid I ANN (BIC) and 6,6% in case of ANN (regr.) and for SP2 does not exceed 34,2% for Hybrid I ANN (BIC) and 34,4% for ANN (regr.). In case of SP3 relative forecast errors for Hybrid I ANN (BIC) does not exceed 34,9% and for ANN (regr.) 39,6%. The results show that the lowest values of relative forecast error (*ex post*) characterize methods that use ANN, especially Hybrid method I and artificial neural networks dedicated to regression.

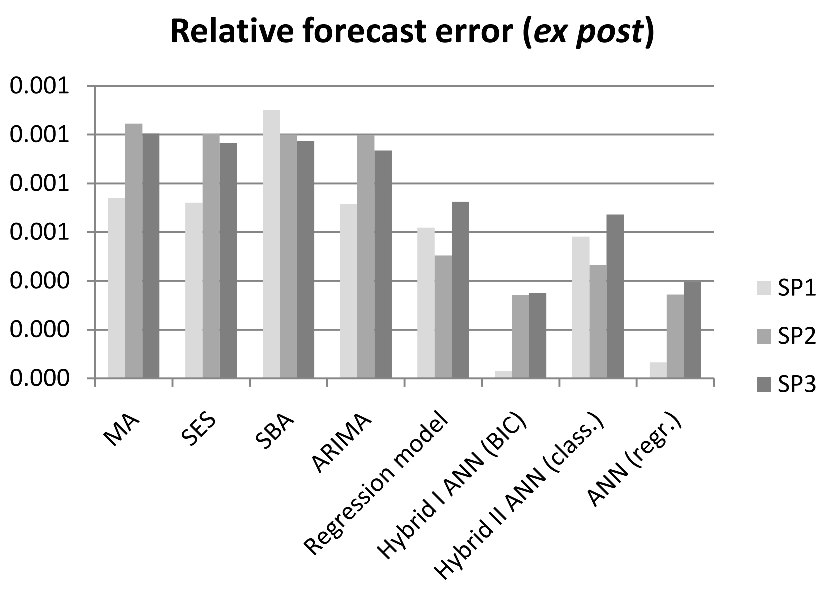

Fig. 3. Relative forecast error (ex post)

5. SUMMARY

In the paper, spare parts demand (lumpy demand) forecasting problem was discussed. Several prediction techniques were presented – both, traditional methods and those based on artificial intelligence. In order to find the most efficient method in lumpy demand prediction, research comparing eight forecasting techniques was conducted. The assessment of analyzed methods was based on comparison of Root Mean Square Errors RMSE and relative forecast errors calculated for all the methods.

Both, RMSE and relative forecast error (*ex post*) showed that the best method, when it comes to spare parts demand forecasting, was Hybrid method I, which was based on econometrical prediction, Schwarz's Bayesian Information Criterion BIC and ANN dedicated to regression tasks. Similar results were obtained for ANN (regr.) approach.

Considering initial steps of the Hybrid method I (BIC, regression analysis, forecast assessment) it can be noticed that from all three analyzed parts only SP2 has acceptable level of relative forecast error. So in this case the forecast assessment may be affirmative and in fact there is no need to construct ANN (BIC). The difference in efficiency of forecasting (between regression model and ANN (BIC)) equals in this case 16%. For SP1 this difference is 60% and for SP3 is almost 38%. This part of the Hybrid method I is simply econometrical prediction. So it is important to underline that economical prediction (and similarly Hybrid method II) is better tool of prediction then other conventional methods, but it is less effective than artificial neural networks dedicated to regression tasks. In order to decide which of those methods could be implemented in a company, a user should decide what is the acceptable level of a forecast error. The difference in efficiency (16%) for SP2 can be evaluated as both – quite high and acceptable. It depends on user's decision. Econometrical prediction is easier to compute, does not need any advanced software. Econometrical models are also easy in interpretation. This is why sometimes it is better to use simpler, but less efficient technique. On the other hand, if the difference in efficiency is large (like 60% for SP1and 38% for SP3), then it is advisable to assess econometrical model negatively and construct artificial neural network (ANN(BIC)). Artificial neural networks however need advanced software, special knowledge and are quite difficult in interpretation. Both methods need a lot of data.

As obtained results show, classical methods like Moving Average MA, Simple Exponential Smoothing SES, Syntetos-Boylan method SBA and Autoregressive-integrated moving average ARIMA were not efficient in demand prediction for each of three analyzed parts. To sum up, obtained results showed that methods that use artificial neural networks are more efficient tools of spare parts demand forecasting than classical techniques. It is advisable to use them as prediction tools especially in companies that are characterized by high machines failure rate. Implementation of efficient prediction technique should significantly support a company in spare parts management issues

HUMAN CAPITAL
NATIONAL COHESION STRATEGY

EUROPEAN UNION
EUROPEAN
SOCIAL FUND

Article is co-financed by the European Union as part of the European Social Fund

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