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THE DESIGN OF FORECASTING SYSTEM USED FOR PREDICTION OF ELECTRO-MOTION SPARE PARTS DEMANDS AS AN IMPROVING TOOL FOR AN ENTERPRISE MANAGEMENT

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Abstract:
This article describes the design of a simple forecasting system and its practical application to predict the sporadic needs for a spare part. The article shows new approach already implemented in the special servicing and production company in Slovakia and its results during a short period of performance after its implementation. Such a proposed model can be a part of the purchase planning of spare parts within the company's logistics system. In some companies, the material flow of spare parts is dominant element in terms of logistics costs. Their management is therefore important for cost optimization, customer satisfaction and market sustainability in a competitive environment. The article, in its introductory part, provides an overview of similar practical solutions within the research of this topic, but many models are designed to be applied in a global market environment and predict the amount of spare parts needed in different industries. However, these models are difficult to use for the needs of a small enterprise, because the main problem lies in the time of a spare part demand rather than its quantity. If there is a need for a specific spare part, which costs several hundred or thousands of euros, but the consumption is only a few pieces per year or more than a year, the time prediction of required spare parts is therefore crucial.

Key words: *forecast, spare parts, time series, order, model*

INTRODUCTION

One of the major logistical challenges in many manufacturing but also in non-manufacturing enterprises is the management of spare parts stock. The problem lays in the great stochasticity of the spare parts requests and therefore setting the optimal level of these stocks requires a scientific approach [1]. But this is just one part of the problem. The second part is to make a decision, whether to have some spare parts in stock indeed. This is the problem concerning high price spare parts, because there is a relatively high amount of funds bonded in spare parts lying long time in stock. The purpose of this article is to describe the methodology by which one company, dealing with relatively expensive spare parts, solved this problem. The problem is relatively unique but there are some authors, who tried to face up to the solution to predict lasting time between present and next order from one customer for the same type of products [2, 3]. Some similar problems were tried to be solved in SME's but with different focus. Forecasting the lead times of production orders was on the basis of past actual lead time data [4]. The main base of information, while creating of forecast of lasting time of customer's order, was also a file of past data of spare parts orders, during the time period of four years. It was agreed by a group of researches and production managers that this period is optimal, because in case of longer period the forecast can be distorted and in case of shorter period the axioms of order appearance could not be detected [5].

The forecasting system is a multi-method model, which is mainly used for the forecasting of sale or consumption. According to the article from authors Keyno-Sadeghi, Ghaderi, Azade, et al. where there is a description of the stochastic consumption of electricity forecasted by the data clustering techniques [6]. Other usage of multi-method model came out from the Chinese automotive industry, provided by authors Zhang and Chen, where there is a kind of comparison model of similar car made [7]. Other complex systems of forecasting use so called fuzzy logic methodology [8], which totally differs from the classical statistical method [9].

As it is mentioned above, many works come out from a different concept but with the similar targets – forecasting. The main aim of this article is to use classical statistical methods for analysing and forecasting ordinary time series even in the time of uncertainty or inherent market volatility. However in a great deal there are used methods of artificial intelligence like a method of neuron networks. Nowadays the usage and the popularity of this method is still increased, however complex problems requires complicated definitions and constructions for solutions [10]. The importance increases when the historical data series have an influence on them as it is shown in the work of [11] to find forecasting of failure rate of industrial cooling equipment.

Consumption of spare parts is very specific from a statistical point of view. Time series are characterized by a high proportion of zero values, which causes problems in the calculations and inaccuracies in solutions. This article presents the predictive model that has been designed for a particular service company of power motion units. The proposed model thus points to a possible solution for a spare parts stock management.

This topic is relatively widespread, and many spare part prediction solutions have been worked out in the world. There is introduced a system of spare part distribution management using simulation, including a predictive model of inventory management with regard to the cost of stockpiles of spare parts in the article from authors Dyntar and Gros, [12]. Compared to forecasting methods, it has acceptable outcomes and reduced the high commitment of funds. However, this model is limited in situations when the total demanded quantity in all simulated periods is extremely high which may cause unbearable time consumption spent on the simulation run. Thus the simulation run has to be substantially accelerated. The simulation itself is also not able to take into account unexpected and rapid demand changes in a way leading to the risk reduction connected with the stock keeping of such item.

Another prediction model of aerospace spare parts management for the aerospace industry based on the known forecasting methods is introduced by authors Wang, Pan, Wang and Wei. The accuracy of the model is evaluated by using so called the grey comprehensive correlation degree [13]. The results show that different situations influence the accuracy of individual methods, but the universality of the solution is missing.

Other authors, in their study have created a forecast based on a time series analysis of spare parts consumption in a dual way: it analyses the linear component by using the ARIMA model, and it analyses the nonlinear component of the time series by using the ANN (Artificial Neural Network) model. The result of the forecast is the combination or the addition of the linear and nonlinear components after these analyses. However, their work is based on the prediction of the consumption of certain spare parts throughout the country like Mexico. The character of the global time series of spare parts need is thus significantly different from data of the specific spare parts need in the concerned company [14].

There are many similar works using the ARIMA and ANN methodologies. Despite these sophisticated methods, which are linked to the concept of high reliability and accuracy, error indicators such as MSE (Mean Square Error) and MAPE (Mean Absolute Percentage Error) show relatively high values. It means that the accuracy of the results is still not sufficient to predict events such as the need or consumption of spare parts.

Probably, this has led authors Qian, Shenyang, Zhijie and Chen to create the predictive model of spare parts consumption using Engineering Analysis Methods [15]. This includes methods such as FMEA (Failure Mode Effect Analysis), FTA (Fault Tree Analysis), FMFRA (Failure Mode Frequency Ratio Analysis) and UFRC (Unit Failure Rate Calculation). However, the calculated results of the accuracy of this model are not known. Nevertheless, the predictive model thus constructed may indicate the direction of creating similar models that are no longer fully mathematical – statistical models. The combination of such solutions with the addition of heuristics satisfies the assumptions of the correct foundations of logistic systems [16, 17].

Quite new methodology is presented by the authors Hasni, Aguir, Babai, Jemai. They presented that the bootstrapping methods have shown a good empirical performance in comparison with classical forecasting methods. It brings reviewing the literature that deals with the bootstrapping approach with discussing some of its statistical properties [18].

There is the overview article by authors Van der Auweraer, Boute, Syntetos, where many published works on Forecasting of spare part demand are analysed with conclusions, that show possible future research directions: 1. Need for collecting the preventive maintenance information in combination with the failure rate information to set up method which combines a broad set of demand drivers; 2. Combination of forecasting techniques can bring a possible research direction as well as further investigation of the combination of extrapolation techniques and causal methods [19].

METHODOLOGY

The time demands transformation into the time series

The task of designing of forecasting model, in this case, is focused to forecast time to obtain a value of time period (a week, a month, a year or even a day), which represents the certain time of anticipated expectation of an order.

The transformation of the characteristics is described in Figure 1. The time line at the top represents an order appearance in last 24 months (from 1/24 to 24/24), i.e. during two-year performance. A thick line means that an order was active in this time, the number represents the number of orders in this period, but this number is not so important. There is a calculation of inactive periods between two active consecutive periods and the result is increased by 1, for better statistic interpretation later. For example between the periods 11/24 and 12/24 the result is “0” and this can cause a mathematical difficulty. These results represent the characteristics of each order and one of them can be drawn as a following graphic representation (chart). The axis ‘X’ represents *the number of appearances – frequency of appearance* and axis ‘Y’ is *the number of inactive periods – interval of appearance* between two active consecutive periods, increased by 1. In principle, this transformation calculates that each following active period is after the calculated period (see Figure 1 as an example) [20].

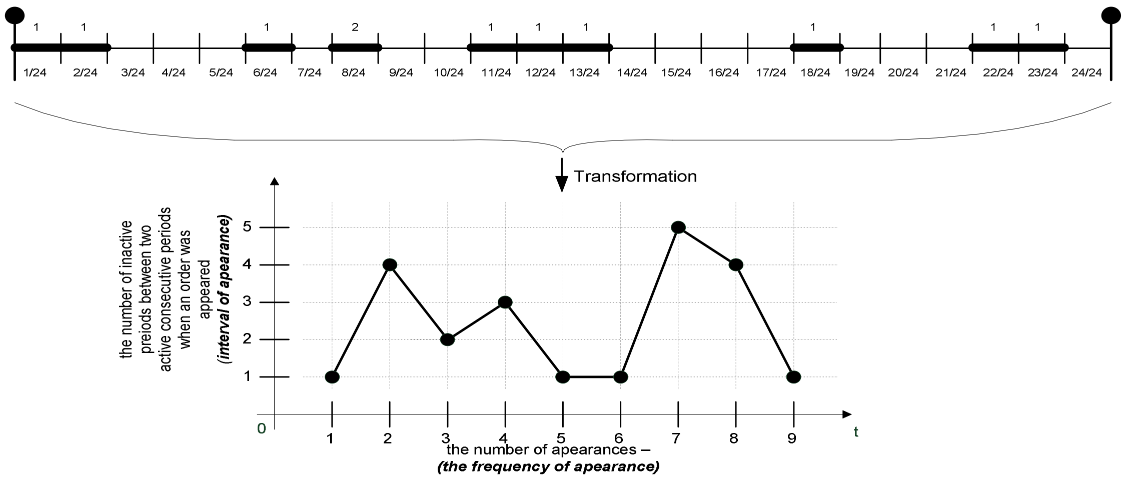

Fig. 1 The transformation of an order appearance periods into time series
Source: [20].

After the transformation of characteristics, the next process of the forecast calculation is provided by the combined model of forecasting.

The combined model of forecasting

This methodology describes the way of combination of results from more forecast calculations into one definite resul. The modern process of forecast calculation is not only based on a result from one method that is why it is essential to combine more results from forecast methods into one definite. The following model or methodology is built on the multicriteria decision and the assessment conception. The aim is to rectify the results from many forecasts into one, which creates consensus of partial results. This also increases the objectivity of the forecasting process. The principle is simple and it uses the weighted average of the partial forecast results and weights are defined according to the MAPE indicator indirectly. The summary of all weights is equal as it is in the following formula (1):

$$\sum_{i=1}^{P} w_i = 1 \tag{1}$$

The following table (Table 1) shows the methods used for forecast calculation and determination of the weights from the MAPE calculation from previous periods.

Table 1
Forecasting methods evaluation by weights for total forecast calculation

Forecasting methods:	**Weights:**
Nonlinear regression (NR)	$w_1 = \dfrac{\frac{1}{MAPE_{NR}}}{MAPE_{NR} + MAPE_{Holt} + MAPE_{ARIMA}}$
Holt	$w_2 = \dfrac{\frac{1}{MAPE_{Holt}}}{MAPE_{NR} + MAPE_{Holt} + MAPE_{ARIMA}}$
ARIMA	$w_3 = \dfrac{\frac{1}{MAPE_{ARIMA}}}{MAPE_{NR} + MAPE_{Holt} + MAPE_{ARIMA}}$

Total forecast (TF) is calculated as weighted average as it describes the following formula (2):

$$TF = F_{NR}w_1 + F_{Holt}w_2 + F_{ARIMA}w_3 \tag{2}$$

where:
F_{NR}, F_{Holt}, F_{ARIMA} – partial forecasts by nonlinear regression, Holt and ARIMA method;
w_i – weights introduced in the Table 1.

THE CASE STUDY DEFINITION

Management of the enterprise, which deals with servicing of specific equipment, distribution and also the procurement of parts, faces the challenge of fast responding to a customer's request. This also requires the management of flow of parts and components. This flow is affected by two factors: the length of delivery times and the cost of spare parts. If spare parts orders are sent to a supplier at the moment of need, it extends the time of customer's order releasing. On the other hand, if the parts are ordered on the basis of keeping the stock level or by the PUSH system, the company's funds are bound to a particular spare part stock. In addition, the release time of a spare part is not known in advance (because of irregularity). This is the core of the biggest problem in the concerned company Motor Drive s.r.o. (the name is intentionally altered) that the lead-time of the required spare parts delivery is too long because of the long-time cycle order to a supplier – delivery from a supplier. Selected types of spare parts are ordered by the company, as a subsidiary, from the Austrian company Watt Drive GmbH, which produces these parts in its own factory overhead. Due to the time of the parent company's procurement, the process of supplying spare parts is relatively time-consuming (Figure 2). This represents a prolongation of the procurement process for the concerned company [21].

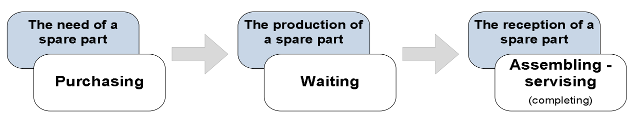

Fig. 2 The process of a spare part order releasing
Source: [22].

Partner companies Motor Drive s.r.o. and Watt Drive GmbH are 520 km far apart from each other (road distance). Their cooperation is based on the lean SCM relationship. Spare part warehouse of the Motor Drive s.r.o. company is internal, shelf, non-automated, located in the company's area and thus in own ownership. Transport of spare parts from Watt Drive GmbH to Motor Drive s.r.o. is provided by a contractual courier and costs are reflected in the prices of spare parts.

The solution of the aforesaid problem is in the creation of the model for forecasting of selected groups of spare parts needs, and then in use of these results to manage spare part stocks. The result of the forecast is the time of anticipated need for a spare part. By subtracting the time of production of order in the parent company, the concerned company will acquire the time of issuing the order for a spare part. This will enable to shorten the process of spare part order releasing in the concerned company, which would add a value to a customer and increase the competitiveness of the concerned company [23].

CALCULATION BY THE INTRODUCED FORECAST SYSTEM

The concerned company Motor Drive Ltd. mediates spare parts but the company itself consumes many kinds of spare parts. Therefore, it is impossible to provide a comprehensive overview of the prediction of all spare parts needs. In particular, the company needed to apply the proposed model for selected spare parts items that are critical in terms of order, consumption, or price. The basis for the forecast calculation is the data on the need occurrence of particular spare parts from previous years.

The drive units, in which the company services maintenance or repairs, consist of an electric motor and a gearbox. That is why the spare parts consist of two main groups. Further, these parts are classified according to the type groups (e.g. depending on motor power). Finally, there is a selection of two specific spare parts from the two main groups on which the proposed forecasting model will be presented. There are selected spare parts and their consumption in the years 2014-2017 in Table 2. After the transformation of these events for the need of a spare part according to the time elapsed between the two nonzero requirements, new time series will be created (Table 3).

Table 2

Consumption of the selected spare parts in 2014-2017

Electromotor power category "90"	Date (MM.YY)	**1.14**	**2.14**	**3.14**	**4.14**	**5.14**	**6.14**	**7.14**	**8.14**	**9.14**	**10.14**	**11.14**	**12.14**	**1.15**	**2.15**	**3.15**	**4.15**	**5.15**	**6.15**	**7.15**	**8.15**	**9.15**	**10.15**	**11.15**	**12.15**
	Shaft (rotor)	0	1	0	0	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0	1
	Winding	0	1	0	0	3	1	0	1	3	1	2	0	1	0	3	0	2	1	0	0	3	1	3	1
	Date (MM.YY)	**1.16**	**2.16**	**3.16**	**4.16**	**5.16**	**6.16**	**7.16**	**8.16**	**9.16**	**10.16**	**11.16**	**12.16**	**1.17**	**2.17**	**3.17**	**4.17**	**5.17**	**6.17**	**7.17**	**8.17**	**9.17**	**10.17**	**11.17**	**12.17**
	Shaft (rotor)	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0	0	0	1
	Winding	1	0	4	0	3	1	0	3	0	0	4	2	1	0	3	0	2	2	0	0	0	1	1	0
Gearbox power category "66"	Date (MM.YY)	**1.14**	**2.14**	**3.14**	**4.14**	**5.14**	**6.14**	**7.14**	**8.14**	**9.14**	**10.14**	**11.14**	**12.14**	**1.15**	**2.15**	**3.15**	**4.15**	**5.15**	**6.15**	**7.15**	**8.15**	**9.15**	**10.15**	**11.15**	**12.15**
	Gearwheel	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	0
	Shaft	0	1	1	0	0	0	1	0	0	2	1	0	1	1	2	0	0	0	1	1	0	2	2	0
	Date (MM.YY)	**1.16**	**2.16**	**3.16**	**4.16**	**5.16**	**6.16**	**7.16**	**8.16**	**9.16**	**10.16**	**11.16**	**12.16**	**1.17**	**2.17**	**3.17**	**4.17**	**5.17**	**6.17**	**7.17**	**8.17**	**9.17**	**10.17**	**11.17**	**12.17**
	Gearwheel	1	2	1	0	0	1	2	0	0	1	0	0	0	0	1	0	0	1	0	0	0	1	1	0
	Shaft	1	1	1	0	2	1	1	1	0	2	1	1	0	1	0	1	1	1	1	1	0	1	0	1

Table 3

Elapsed time (in months) between two consecutive periods of a SP need

Electromotor power category "90"	Nr. of occurrence	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**		
	Shaft (rotor)	2	3	7	1	3	4	4	1	11	2	4	6	-	-	-		
	Winding	2	3	1	2	1	1	1	2	2	2	1	3	1	1	1		
	Nr. of occurrence	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**		Average quantity per occurrence:
	Shaft (rotor)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	Shaft (rotor)	1
	Winding	1	2	2	1	2	3	1	1	2	2	1	4	1	-	-	Winding	2
Gearbox power category "66"	Nr. of occurrence	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**		
	Gearwheel	2	11	2	8	2	1	1	3	1	3	5	3	4	1	-		
	Shaft	2	1	4	3	1	2	1	1	4	1	2	1	2	1	1		
	Nr. of occurrence	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**		Average quantity per occurrence:
	Gearwheel	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	Gearwheel	1
	Shaft	2	1	1	1	2	1	1	2	2	1	1	1	1	2	2	Shaft	1, recommended: 2

These are the subject of forecasting, the result of which is the period of assumption of the demand occurrence for a particular spare part (SP).

The graphical representation of the demand occurrence intervals for particular spare parts (Figure 3) helps to select appropriate forecast methods [24].

Because the spare parts requirements are stochastic, the choice of forecasting methods will be taken towards the methods that have the character of smoothing of acquired data interval for the occurrence of spare part requirements except ARIMA – this method was chosen according to the general accuracy. For this reason, these forecast methods were chosen: regression analysis, Holt method and ARIMA. The forecast will be carried out in two ways:

1. From the 2014-2016 data and forecast for 2017 and then the MAPE accuracy indicator and the correlation coefficient will be calculated.
2. From the 2014-2017 data and forecast for 2018. Because the actual values from year 2018 are not known, the MAPE accuracy indicator or the correlation coefficient will be calculated from years 2014-2017.

Forecast 2017

There was also calculated Total forecast from the three aforementioned forecast methods by weighted average (WA). There were used weights according to the MAPE indicator in indirect form. For example: the ARIMA method has the highest accuracy (the lowest MAPE), it means the higher weights at WA calculations. The weights were calculated proportionally and the sum is equal to 1. The forecast results are in the following diagrams and Table (Figure 4 and Table 4).

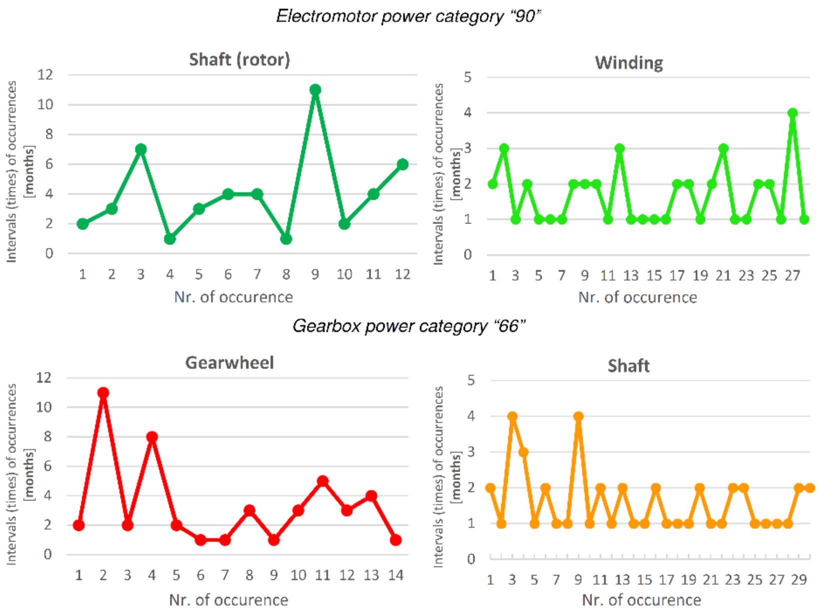

Fig. 3 Diagrams of spare parts demand occurrence intervals

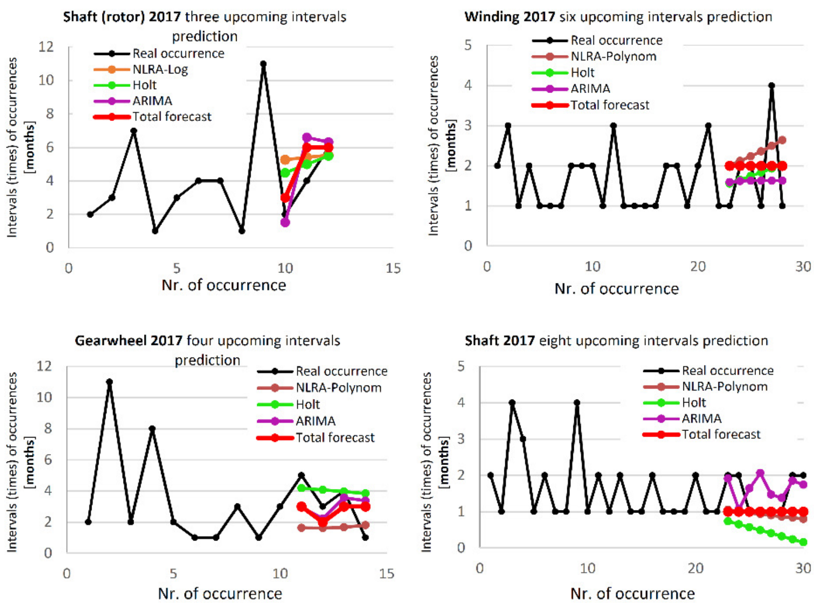

Fig. 4 Diagrams of spare parts occurrence forecast for the year 2017

Table 4

The MAPE indicator of accuracy when forecast for the year 2017

Model (method)	Spare p.	MAPE	Spare p.	MAPE
Nonlinear regression	Shaft (rotor)	89.85%	Windings	49.78%
Holt	Shaft (rotor)	72.79%	Windings	47.60%
ARIMA	Shaft (rotor)	38.69%	Windings	34.11%
Total forecast	Shaft (rotor)	53.70%	Windings	45.68%
Nonlinear regression	Gearwheel	88.65%	Shaft	40.79%
Holt	Gearwheel	136.65%	Shaft	57.45%
ARIMA	Gearwheel	67.34%	Shaft	42.80%
Total forecast	Gearwheel	75.92%	Shaft	40.80%

The total forecast is rounded to integral numbers. If the predicted occurrence was earlier than real demand, a spare part remains in stock and the next predicted period is ignored until the real demand occurs. If the predicted period was later than real demand, order for a spare part is sent immediately and forecast may be corrected.

Forecast 2018

The rule for total forecast calculation was the same as in the previous case. The forecast results are in the following diagrams and table (Figure 5 and Table 5).

The same rule of stock management was applied for the year 2018. In case of predicted occurrence, determined quantity, from the table 2, was ordered to satisfy customer demand.

Table 5

MAPE indicator of accuracy when forecast for the year 2018

Model (method)	Spare p.	MAPE	Spare p.	MAPE
Nonlinear regression	Shaft (rotor)	79.32%	Windings	45.89%
Holt	Shaft (rotor)	72.89%	Windings	48.10%
ARIMA	Shaft (rotor)	34.47%	Windings	40.12%
Total forecast	Shaft (rotor)	40.82%	Windings	44.44%
Nonlinear regression	Gearwheel	97.26%	Shaft	43.06%
Holt	Gearwheel	136.79%	Shaft	47.46%
ARIMA	Gearwheel	77.67%	Shaft	38.59%
Total forecast	Gearwheel	96.30%	Shaft	41.84%

DISCUSSION

There are a number of macroeconomic and microeconomic factors that can more or less influence the course of cooperation with the supplying company on one side and customers on the other side. After analysis with experts from Motor Drive s.r.o. it was concluded that macroeconomic factors such as: GDP growth and unemployment declination have an impact on the growing purchasing power of the population, resulting in higher demands on production facilities and ultimately increasing demand for spare parts. Unfortunately, the stochasticity in the requirements for spare parts is so high that it is not possible to define a clear relationship between these parameters.

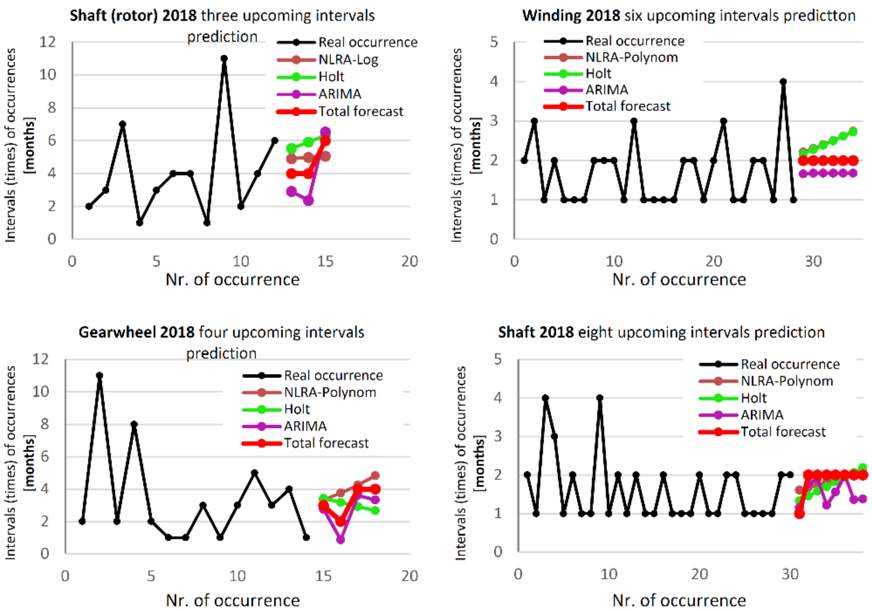

Fig. 5 Diagrams of spare parts occurrence forecast for the year 2018

However, this relationship is reflected in the frequency of demand for a particular spare part, what is used in the proposed model. The price of offered spare parts has not yet played a major role in demand, the price is relatively stable and unless customers are contemplating investing in new technologies, they will continue to use the services of the service company Motor Drive s.r.o. Spare parts are provided to a wide range of specific industrial machines, to many customers and that is why it is difficult to define the life cycle position. This is the responsibility of the customer care department and in case of changes this information is forwarded to the planning department after the recommendation.

Spare parts storage in each company brings losses in the form of locked-up money in the stock of spare parts. On the other hand, readiness is high when a device is promptly repaired, but it requires a needed spare part on hand. Although the above proposed system cannot behave as the JIT system, i.e. it is unable to set a high flexibility and readiness at zero cost (zero locked-up money in the stock of spare parts). This is not the aim of the system, because it would be impossible to reach due to the high volatility of devices failure. This is also evidenced by the relatively high MAPE values calculated based on the initial experience of using the proposed system (Table 5). However, even when studying articles on solving similar problems, the reported MAPE values are also quite high, in many cases far above 50%.

In particular, the aim of this proposed system is to contribute for uncertainty reducing and, based on used forecasting methods, for finding the probable time of occurrence of the particular spare part (SP) replacement requirement. Anyhow, such a system is easy to implement and apply to various operations and businesses with similar problems. The simplified algorithm of the proposed system is as follows (Fig. 6).

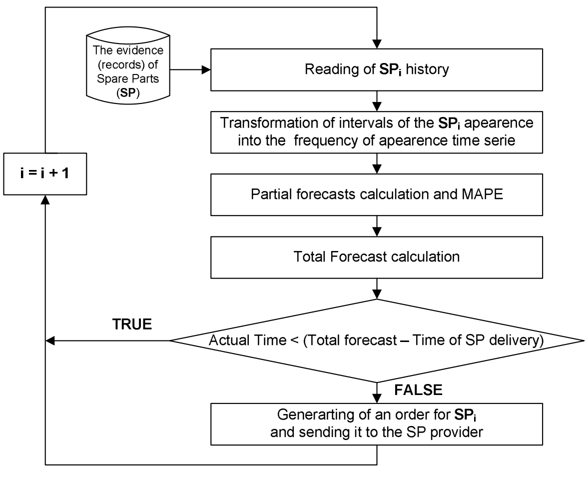

Fig. 6 Simplified algorithm of the proposed system

CONCLUSION

Despite the mentioned randomness of demand for spare parts, ARIMA showed the most accurate results from the demand forecast, of selected spare parts in both groups in average. It has been suggested that the results of this method are considered with high priority for the company. According to the latest information, this model has brought shorter order release times of spare parts up to 37% and adequate savings of locked-up costs, what the company considers to be a success.

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