



FORECASTING NEEDS OF THE OPERATIONAL ACTIVITY OF A LOGISTICS OPERATOR

Mariusz Kmiecik, Maciej Wolny

Silesian University of Technology, Zabrze, Poland

ABSTRACT. Background: The paper considers the issue of operational needs of logistics operator connected with the implementation of demand forecasting tool in his activity. The aim of this article is to present research results on the ability to meet the expectations of distribution centre managers at the operational level. To achieve the main goal, three research questions concerning general requirements and possibilities of meeting the requirements set by managers working for a logistics operator were also defined and related to operational needs.

Methods: The research analysed the operational requirements of a logistics operator using a survey conducted among managers dealing with the operational work that is performed in the operator's warehouses. Then, the possibility of implementing and operating a forecasting tool based on the ARIMA algorithm in the logistics service of a confectionery manufacturer was analysed, providing the verification of usefulness of such a tool and the level of its adjustment to operational requirements.

Results: The forecasting tool is especially useful in the operator's activity in order to support the resource planning process of warehouse operation. However, managers set high requirements regarding the verifiability of the operation of such a tool, which is not completely available in the current situation. The article also shows the future development paths of this tool.

Conclusions: The article shows possibilities related to the use of a forecasting tool in activities related to the provision of services in contract logistics. This allows for verification of the needs and capabilities of the logistics operator who would forecast the demand to support the operations it carries out.

Keywords: 3PL, logistics operator, demand forecasting, distribution network

INTRODUCTION

In distribution networks and other economic practices, it can be concluded that an event will occur if [Alevizos et al. 2018]: it has already occurred in the past, its occurrence frequency would indicate it, or is indicated by a strong correlation with another event or events that have already occurred or are going to occur. The phenomena occurring in the systems can be defined by means of quantitative (expressed in quantities) and qualitative (expressed in descriptive terms) variables. Forecasting is the process of determining the most likely prediction of the future level of demand with a given set of assumptions [Moon, 2000] consisting in statistical inference integrated with the analysis of events, phenomena and facts that have

happened in the past. The methods and types of forecasting are a frequently discussed area in the literature. There are many criteria and many attempts to group the methods in it. And so: one of the more general characteristics of forecasting models assumes their division into 3 main, most significant types: judgemental forecasts, cause-and-effect forecasts and forecasts based on the analysis of time series. The main purpose of forecasting is to support decision-making processes, and the forecast itself is an action that is to prepare other activities, and therefore lead to the path choice the enterprise wishes to follow.

Forecast is considered a necessary source of information for the preparation of logistics plans [Panahifar et al. 2015], including plans related to distribution and cooperation in distribution networks, and inventory in both distribution

networks and supply chains should usually be treated as the final mechanism to balance supply and demand [Szozda and Świerczek 2016; Westcott 2004]. Forecasting is considered to be one of the key elements of organisational management and one of the risk categories [Kramarz, 2013; Morris et al. 1988] in material flows. It affects the determination of production capacity and methods of production and provision of services and thus also affects elements such as the number of employees, the level of costs, etc. indirectly. The risk factors related to forecasting are: their imprecision, seasonality, product differentiation, short product life cycle, small customer base, and information distortion [Kim et al. 2012; Subramaniam, 2021]. Demand fluctuations may imply problems with inventory management and create a tendency to maintain excessive inventories (this briefly applies to each type of inventory, i.e., cyclical, safety, in transit, and speculative inventory [Barlas and Gunduz 2011]). Forecasts are always burdened with some errors. They never describe a given phenomenon with 100% accuracy. The uncertainty of demand forecasts arises from facts indicating that enterprise will never have complete information on buyers, competitors' initiatives may affect the actions taken, and the environment is uncontrolled by the company and may change [Alevizos et al. 2018]. Forecasting is undoubtedly useful in the case of Make-To-Stock (MTS), but it can also be used in the case of Make-To-Order (MTO) to forecast e.g. standard components [Kalantari et al. 2011]. Forecasts in the distribution network determine the quantity of goods to be purchased, produced, or delivered. Forecasts create related processes and operations. Forecasting is of particular importance as one of the means that is used in the process of managing a business, because wrong identification of future trends can have devastating implications for the enterprise. For example, overestimating demand can result in high costs of maintaining excess inventory and high marketing costs for disposal [Martin et al. 2020]. Whereas, for example, underestimating can have such effects as lost sales, loss of reputation and lower level of sales tasks. Knowing about future supply quantities significantly improves planning in all areas of logistics, and the use of flexible and precise forecasting procedures gives the opportunity to obtain good results even in capricious markets,

where the practice of ordering through intermediaries distorts the demand of end participants (Subramaniam, 2021). One of the functions of the enterprise that forecasting supports is planning and resource management. It is often considered a strategic decision of the company in the area of material resource planning [Wacker and Lumus 2002], but also for human resource planning for work in logistics and production systems [Berk et al. 2019].

However, it should be remembered that the quality of the forecast depends on the process in which the forecasts are formed, as well as its accuracy and [Panahifar et al. 2015]: division of responsibility for forecasts, creation of appropriate forecast formats (horizon, division into periods, frequency of updating, level of detail), methods for measuring said accuracy, and providing a method for converting the forecast to a demand forecast for the entire network and individual elements. As is known, making a forecast is a multistage process [Williams and Waller 2011], which leads to the identification of an appropriate forecasting method on the basis of which further plans will be built. The forecasts themselves are usually input into the demand management system. Demand management is also defined as the process of estimating future demand volumes in order to synchronise activities within a certain enterprise (manufacturing, trading, or service) [Croxton and Lambert 2002]. Demand management facilitates the optimisation of the available capabilities [Broberg and Persson 2015], and is also considered by some authors to be one of the basic processes of the Supply Chain Management (SCM) concept. Many problems that occur in distribution networks directly are believed to be the implication of malfunctioning demand management processes [Fahroiglu and Alvarado 2001]. Thus, it can be concluded that a well-chosen demand management system has a positive impact on the enterprise, but also on its suppliers and customers [Croxton 2002]. The goal of demand management is not so much to generate sales as to provide a set of activities for the most advantageous options [Świerczek 2019; Croxton and Lambert 2002] and focusing on balancing customer requirements with the capabilities of the distribution network.

The aim of this article is to present research results on the ability to meet the expectations of

distribution centre managers at the operational level. The starting point is a survey conducted among managers on preferences and expectations in relation to forecasts (what characteristics should the forecast have). The main research questions posed in the article:

RQ1: What requirements does a logistics operator have of the forecasting system in the perspective of its implementation in its operational activities?

RQ2: What benefits to the operational activity of a logistics operator can the implementation of a system for the automatic creation of demand forecasts bring?

RQ3: Is it possible to meet the identified operational requirements of a logistics operator by implementing a forecasting tool in the current form of the operator's operations?

The purpose of the article and the responses to the individual research questions were analyzed on the basis of an analysis carried out at the chosen logistics operator.

METHODS

For the purposes of this article, 60 people who act as operational managers related to warehouse, copacking, and co-manufacturing processes were analysed. The group of chosen managers emerged from the 71 managers who work in the chosen logistics operator. The main

research group (71 workers) is the workers which have experience in the logistics management field above 1 year and at least 4 years of experience in the work in warehousing logistics. Managers are handling with the processes connected with the operational warehousing activity which are provided by logistics operator like co-packing managing, picking managing and so on. The authors assumed the significance level at 0,05, predicted fraction size as 50% and allowed error as 5% - according to this assumption, the 60 surveyed managers are the enough research sample to conduct the research. These people are directly involved in the operational work in the warehouse and carry out their continuous control. The aforementioned managers are part of the organisational structures of the 3PL logistics operator (third-party logistics). 43 managers (72%) operating in Poland, 11 managers (18%) operating in the Czech Republic, and 6 managers (10%) operating in Slovakia were examined.

The aforementioned logistics operator provides logistic services related to the operation of warehouses, logistic processes, copacking, co-manufacturing, cross-docking and the creation of new logistic solutions for production enterprises. Logistics operator is the international company that provides logistics services (mainly warehousing and creating the added value) for its contract partners (usually manufacturers). Figure 1 shows a simplified diagram of the flows from the producer to the end customer using the operator.



Fig 1. A simplified diagram of material flows in the distribution network using the use of a logistics operator
Source: own elaboration

The logistics operator does not take ownership of the products that are in its warehouse. It conducts logistic flows for the producer as part of contract logistics. The main

steps in the article are shown in Figure 2. In this article, terms such as: logistics operator, 3PL, third-party logistics and logistics service provider will be used with the same meaning.

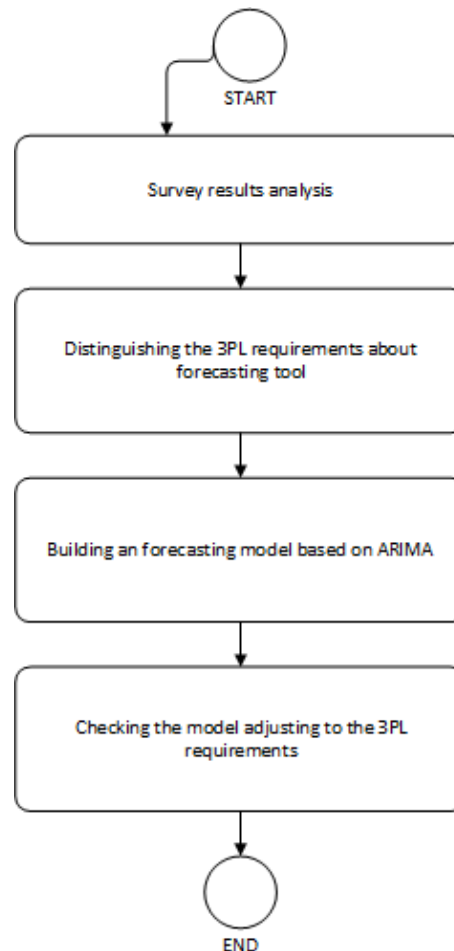


Fig 2. Main research steps

Source: own elaboration

The research was conducted in two stages:

1. Based on the results of the survey, the requirements (expectations of a characteristic) that should be met by the forecasts were defined. In the analysis of the survey results, the following significance level was adopted: 0.05.

2. For the chosen producer (showing the largest variety of products), it was examined to what extent it was possible to meet the expectations of managers.

The first stage concerned the creation and execution of a survey among managers who deal with the management in the operational area of the logistics operator's operations directly. The following questions were created:

Question 1. What degree of aggregation of the forecasting data would correspond to the preferences of operating activities?

Question 2. In what area do you see the greatest chances of using the forecasting tool?

Question 3. What is the maximum error rate for one week (as a percentage) for which the forecast can be considered useful?

Question 4. Please indicate a single most important criterion for the assessment of the forecasting tool in your opinion.

Question 5. Please specify the amount of time that you currently spend daily on inventory planning.

The questions were aimed at identifying the needs of a logistics operator in terms of the possibility of using a forecasting tool in its operational activities and identifying the tool main requirements of the users in the area of data aggregation, the maximum error rate, as well as the measure that should be adopted to measure forecast errors. Furthermore, the survey asked how much time respondents currently spend on planning inventory resources, to also show the potential of using a forecasting tool to improve the resource planning process.

The research in stage 2 covered the following issues: selection of an automatic forecasting model, testing of the selected model, and conclusions on the fit of the model to the

operational requirements of a logistics operator. The tests used a cloud-based tool which made the development of forecasts possible based on the ARIMA model supported by elements of machine learning developed by the authors of the programme. The results of these calculations are presented in the article, and then the results were confronted with the operational requirements identified during the survey.

RESULTS

The responses obtained through the survey were analyzed. The first question was related to the degree of aggregation of the forecast, which related the preferences of managers on this topic (Table 1).

Table 1. Answers to question No. 1.

Question 1. What degree of aggregation of the forecasting data would correspond to the preferences of operating activities? [multiple choice questions]		
Responses	Number of responses	Shares in total responses
Daily forecast for total boxes	47	78,33%
Weekly forecast for total boxes	36	60,00%
Daily forecast of boxes for individual SKUs*	13	21,67%
Weekly forecast of boxes for individual SKUs	16	26,67%
Daily forecast of boxes for individual SKUs, broken down by end recipients	16	26,67%
Weekly forecast of boxes for individual SKUs, broken down by end recipients	13	21,67%
Forecast for amount of pallet space	33	55,00%
Forecast in cubic metres	12	20,00%
Other	3	5,00%
*SKU – Stock Keeping Units		

Source: own elaboration

Boxes are understood as the smallest logistic item that is manipulated in the warehouse. When analysing the answers, the respondents most often stated that the most useful forecast from their point of view would be an aggregated forecast for the total quantities issued from the warehouse, without the need to disaggregate it into a forecast of the size of individual SKU (Stock Keeping Units) or issues to individual destination points (end recipients).

The aggregated data was reflected by the largest number of responses, i.e. :

- Daily forecast for total boxes (78.33%).
- Weekly forecast for total boxes (60.00%).
- Forecast for the amount of pallet space (55.00%).

More than half of the respondents indicated only the daily forecast of total boxes, to a significant degree (X-squared = 18.15, df = 1, p-value = 1.021e-05 in one-tailed, 1-sample proportions test with continuity correction). In the case of weekly forecast, about half of the respondents considered this form of aggregation to be preferred (X-squared = 2.0167, df = 1, p-value = 0.1556 in two-tailed, 1-sample proportions test with continuity correction). Similar results were obtained regarding the forecast for the amount of pallet space (X-squared = 0.41667, df = 1, p-value = 0.5186 in the two-tailed, 1-sample proportion test with continuity correction). Other forms of aggregation are significantly preferred by less than 50% of the respondents.

Other responses related to the aggregation of the forecast results concern the responses related to the forecast in cubic meters. Considering that by adding parameters related to palletisation and dimensions of the boxes, it will be possible to extend the forecast in the future after the count of boxes with the forecast for the amount of pallet space or cubic space, according to the authors, the best solution in the first step would be to develop a collective forecast for the number of boxes, which are issued from the warehouse on individual days. The answers to the next question are presented in Table 2, and these were single choice answers.

Table 2. Answers to question No. 2.

Question 2. In what area do you see the greatest chances of using the forecasting tool?		
Responses	Number of responses	Shares in total responses
Planning of warehouse resources (number of employees, equipment) for working shifts.	47	78,13%
Planning of transport operations.	8	13,00%
Planning of the warehouse assortment (e.g., support for classic ABC / XYZ methods)	3	5,00%
Correcting forecasts provided by customers	1	2,00%
Other	1	2,00%

Source: own elaboration

The second question concerned the main area of application of a forecasting tool in the operational activity of a logistics operator. Most of responses (78.33%) were related to the use of the forecast results as a tool to support the planning of warehouse resources. Planning of warehouse resources is understood as the need to define in advance an appropriate number of warehouse employees, the necessary warehouse infrastructure (e.g. forklifts, data collectors) to support ongoing warehouse operations. As shown from the results of the questionnaire, the forecasting tool should focus primarily on the fulfilment of this need. The next question was about the maximum error rate that is acceptable in operational activities. Based on the answers of the respondents, it can be concluded that:

- Up to 2% forecast error will meet 100% of operational needs.

- Up to 3% forecast error will meet 92% of operational needs.

- Up to 5% forecast error will meet 88% of operational needs.

- Up to 10% forecast error will meet 50% of operational needs.

- Up to 20% forecast error will meet 7% of operational needs.

Based on the results obtained, errors of 5%, 3%, and 2% were adopted as the key accuracy levels for the forecasts.

The next table (Table 4) contains answers to the fourth question.

Table 3. Answers to question No. 3.

Question 3. What is the maximum error rate for one week (as a percentage) for which the forecast can be considered useful?		
Responses	Number of responses	Percentage of requirements meeting (forecasts lower or equal to response)
Up to 2%	5	100,00%
Up to 3%	2	91,67%
Up to 5%	23	83,33%
Up to 10%	26	50,00%
Up to 20%	4	6,67%

Source: own elaboration

Table 4. Answers to question No. 4.

Question 4. Please indicate a single most important criterion for the assessment of the forecasting tool in your opinion.		
Responses	Number of responses	Shares in total responses
The smallest possible deviation of the forecast values (in total) for a given week of dispatches compared to the real value (MAE* for 1 week).	9	15,00%
The smallest possible deviation of the forecast values (in total) for two weeks in advance compared to the real value (MAE for 2 weeks).	11	18,33%
The smallest possible average of the daily percentage differences between the forecast and the real dispatch levels of each week (MAPE** for 1 week).	25	41,67%
The largest possible number of well-matched (with the smallest percentage of deviations) forecasts in individual weeks.	14	23,33%
Other	1	1,67%
*MAE - Mean Absolute Error		
**MAPE - Mean Absolute Percentage Error		

Source: own elaboration

This question involved the development of a criterion for the evaluation of a forecasting tool. From the analysis of the results and the comparison of the results with previous responses, it can be concluded that the forecasting tool should return the forecast on a daily basis, and errors should be considered in the perspective of a week; it is related to the fact that warehouse resources must be planned at

least one week in advance, and large modifications of daily resources are not acceptable. In Question number four, most responses revealed that the lowest MAPE error criterion was for 1 week. Therefore, the authors will use the forecast assessment criteria related to the minimisation of the weekly error along with the minimisation of the differences generated by the daily forecasts that relate to the actual data. Table 5 shows the answers to the next survey question.

Table 5. Answers to question No. 5.

Question 5. Please specify the amount of time that you currently spend daily on inventory planning.		
Responses	Number of responses	Shares in total responses
Up to 10 minutes	12	20,00%
Up to 30 minutes	28	46,67%
Up to 1 hour	13	21,67%
Up to 1.5 hours	5	8,33%
Up to 2 hours	2	3,33%
More than 2 hours	0	0,00%
Other	0	0,00%

Source: own elaboration

This question was to determine the amount of time each day managers spend on inventory planning. By using the sum of the products and dividing it by the sum of the expected results, it can be estimated that the correct creation, implementation and integration of a forecasting tool will reduce the workload of managers by 29.83 minutes. In turn, this translates into the possibility of reducing their working time on a weekly scale (with a five-day work system) by about 149.15 minutes, and on a monthly basis (assuming an average four-week working month) by about 9.94 hours. It is worth emphasising that although resource planning is not an activity that generates added value, it is necessary for correctly implemented warehouse processes, and therefore its shortening will positively affect the entire operational activity of a logistics operator.

Implementation of the forecasting model to the activities of a logistics operator is possible [Kmiecik 2021], but it requires adjusting the tool to the operator's existing IT infrastructure; in addition, it is also possible for the operator to take over the distribution network coordination function consisting in the use of a forecasting tool, including for conducting stock management actions [Kramarz and Kmiecik 2022]. However, an important part of the operation of a logistics operator will be the ability to adjust the operation

and results of the forecasting tool to its current needs, in accordance with the requirements of operational managers. The forecasting tool would be used to aid the current logistics operator's efforts to plan warehouse resources by providing the necessary demand information in advance. This tool would have to:

- Provide the possibility of aggregating forecasts in at least three levels: daily forecast for the total of boxes, weekly forecast for the total of boxes, forecast for the amount of pallet space.
- Provide the ability to create forecasts with the MAPE forecast error at the lowest possible level.
- Be based on minimising the weekly MAPE in the forecast analysis.

The authors of this article decided to use a forecasting algorithm based on the ARIMA model to construct the forecasts. This choice was dictated by the fact that ARIMA models are those that are among the most frequently chosen in research for forecasting demand [Sohrabpour et al. 2020; Chu and Zhang 2003], even as a basis for more sophisticated models related to neural networks [Omar et al. 2016]. The authors created a forecasting tool on a ready-made model based on ARIMA (Figure 3)

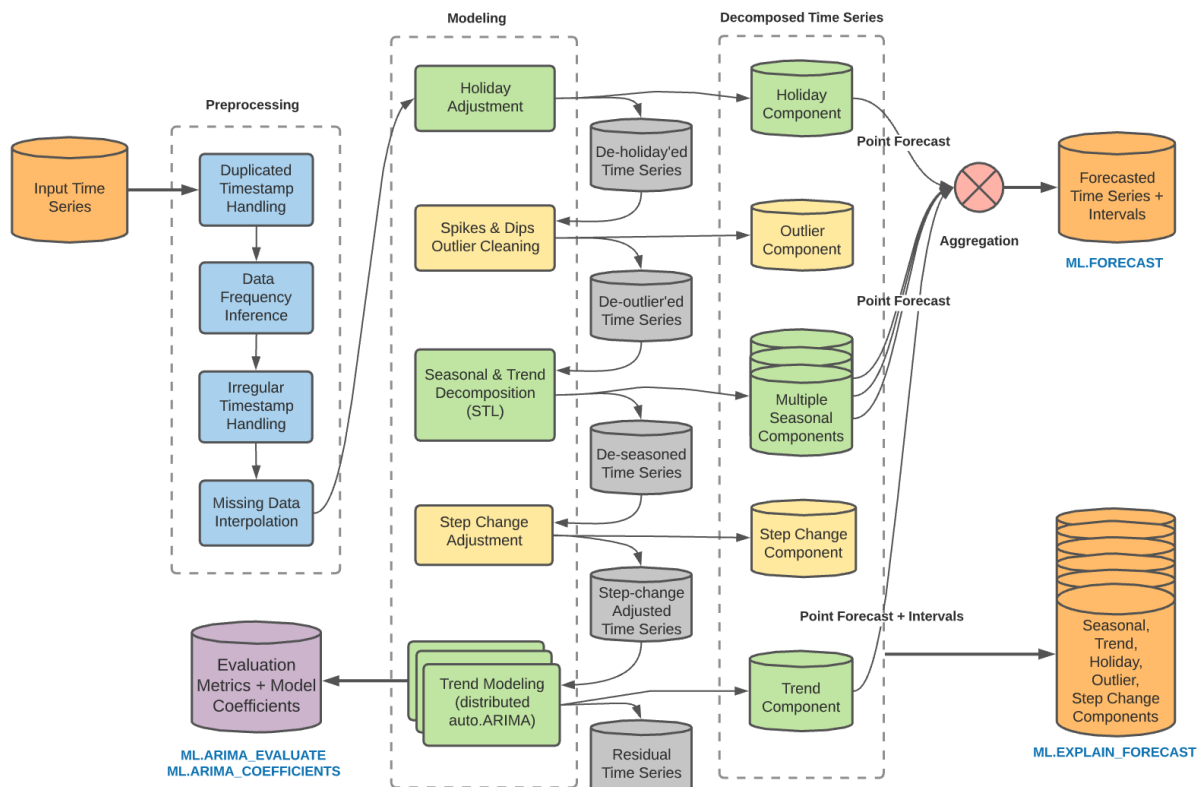


Fig 3. Operation of the selected ARIMA-based model

Source: Google Cloud Documentation (<https://cloud.google.com/bigquery-ml/docs/reference/standard-sql/bigqueryml-syntax-create-time-series>) [accessed: 10/02/2022]

The model used allows for applying auto frequency to input data, dealing with irregular time intervals, duplicate data, analysing and reducing outliers, and applying the holiday effect.

The analysed data cover a total period of 594 days (86 full weeks) and concern products of a producer operating in the confectionery industry. Data consist of the date related to the activity of the logistics operator in the warehouse, the number of cardboard boxes dispatched, and the amount of pallets that have been prepared and released from the warehouse to the recipient (Figure 4). The data therefore allow for aggregation of the forecast at the level of total boxes and total pallets on a daily and weekly basis.

The analysis was based on the calculation of forecasts in a weekly horizon, assuming that

the input data for the analysis was updated once a week. The test period was the last 20 weeks (Figure 5).

The calculation was performed each time using the training set, to which another week was added to calculate the MAPE until the test data limit was reached, i.e. 20 weeks. The matching of the forecasts created in this way is shown in Figure 6.

Additionally, to better show the adjustment of ex post forecasts to the historical time series, Figure 7 only shows graphs reflecting the test periods of time series and the size of forecasts in relevant periods, without taking into account weekends and holidays for which no dispatches were observed and for which no dispatches were planned.

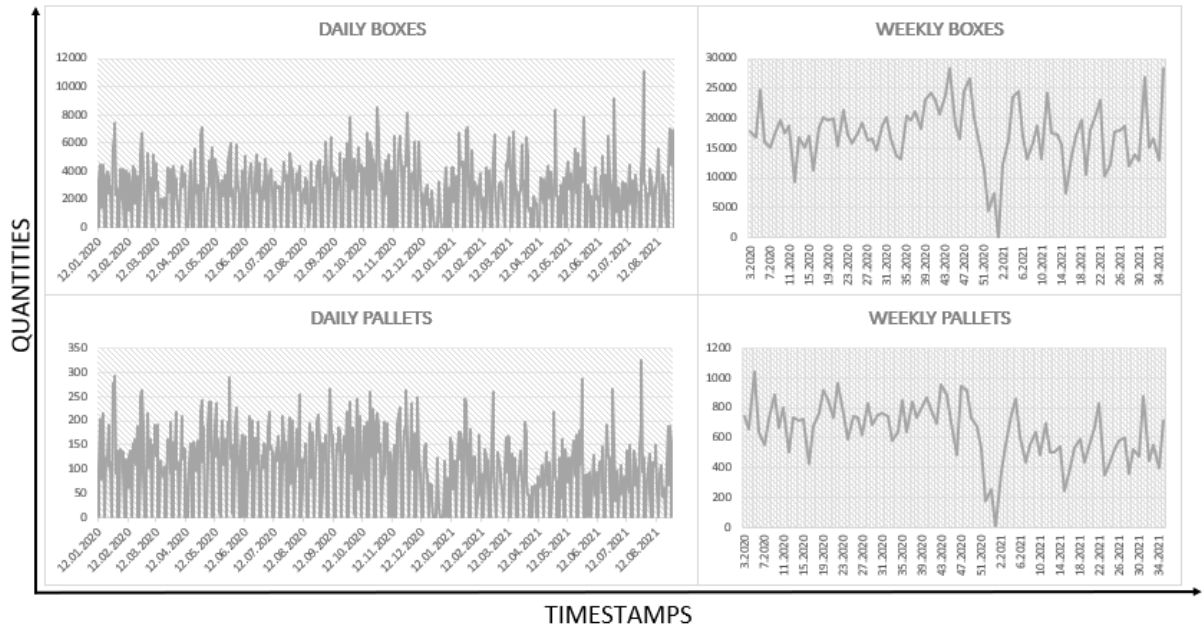


Fig 4. Time series used in the analysis

Source: own elaboration

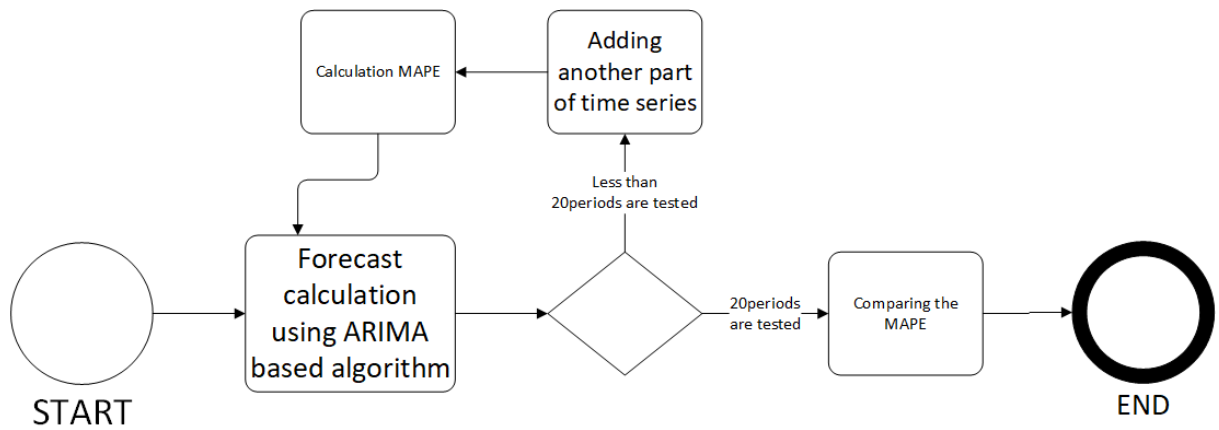


Fig 5. Simplified diagram of the analysis

Source: own elaboration

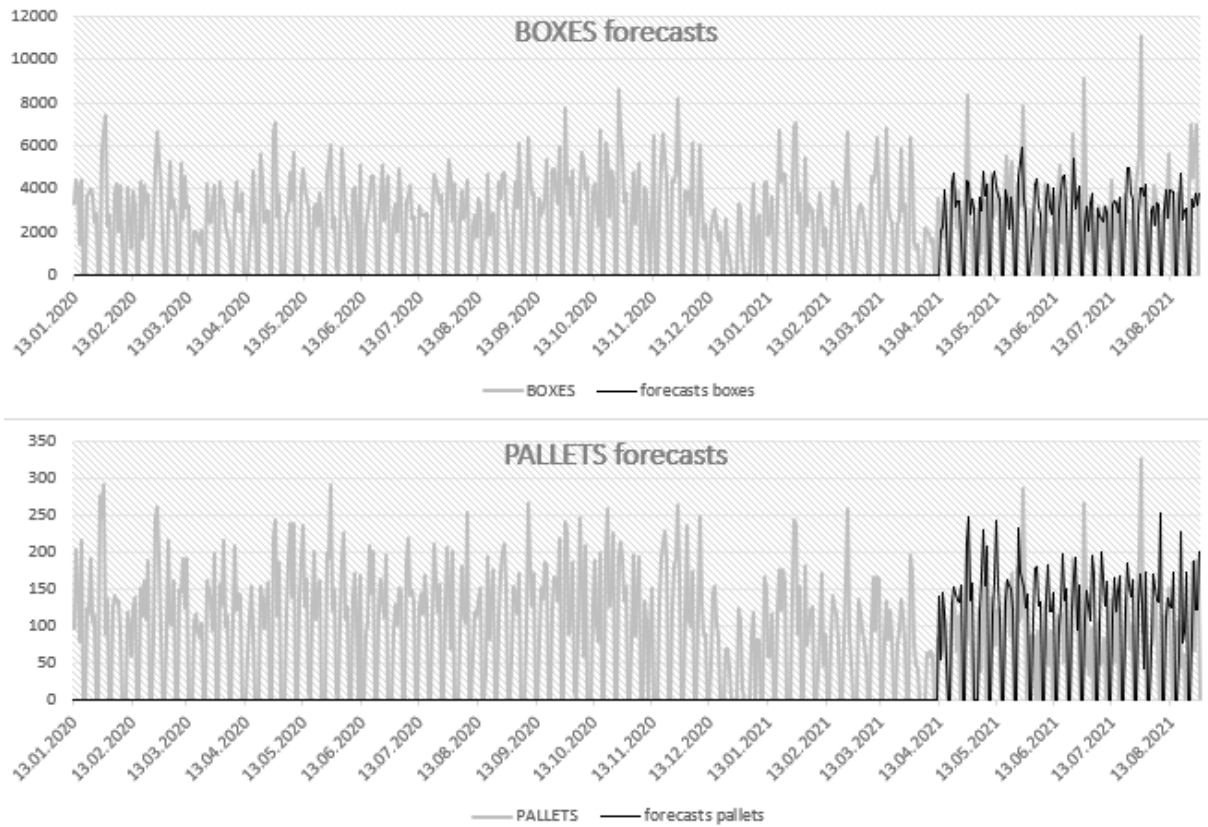


Fig 6. Matching forecasts in boxes and pallets

Source: own elaboration

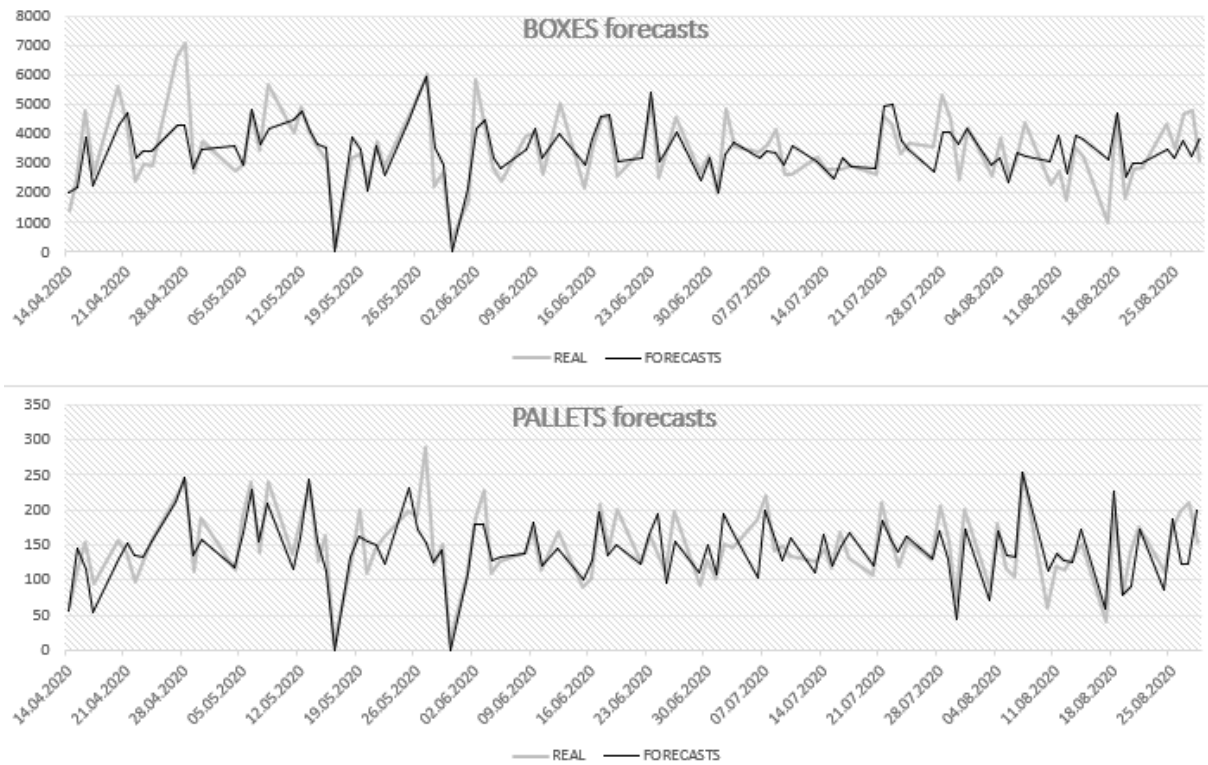


Fig 7. Matching forecasts to test data without weekends and holidays

Source: own elaboration

As the analysis shows, the algorithm used is good at detecting fluctuations in demand and detecting the trend in the time series. According to the requirements presented on the basis of the analysis, the MAPE survey was aggregated into weekly periods (Figure 8).

Based on drawing and analysis, it can be concluded that the average MAPE size covering 20 weeks for boxes is 13.51%, and for pallets 13.04%. Forecast results for both data aggregation units are similar, which indicates the repeatability of the algorithm's operation and its

best results accomplishment that could be achieved with the given assumptions. The best forecast result in the test period, which would meet operational requirements in 88%, was achieved in 5% of the forecasts (Table 6).

As the analysis shows, in the current configuration, despite the seemingly high result and a good match of the forecasting algorithm to the data, as much as 15% of the created forecasts would not meet the operational requirements and only about 40% of the forecasts would meet approximately 50% of the requirements.

Table 6. Comparison of weekly MAPE and operational requirements

Characteristics of forecasts	Percentage of forecasts in test periods	
	BOXES	PALLETS
Meet the requirements of 100%	0.00%	0.00%
Meet the requirements of 92%	0.00%	0.00%
Meet the requirements of 88%	5.00%	5.00%
Meet the requirements of 50%	40.00%	35.00%
Meet the requirements of 7%	85.00%	85.00%
Don't meet the requirements	100.00%	100.00%

Source: own elaboration

DISCUSSION AND CONCLUSIONS

The forecasts developed by a logistics operator in its operational activities may be of greatest importance in the area of supporting warehouse resource planning. The currently proposed forecasting algorithm meets the assumption of creating automatic forecasts and the assumption related to the possibility of aggregating forecasts in terms of daily and

weekly forecasts. Additionally, the proposed solution makes it possible to create forecasts for boxes and pallets, in accordance with operational requirements. The article also shows a comparison of MAPE for the created forecasts. The results were mainly related to the average weekly errors and compared with the operational requirements of the logistics operator. The biggest issue with operating the forecasting tool is the problem of insufficient adjustment of forecasts to operational requirements (Figure 9).

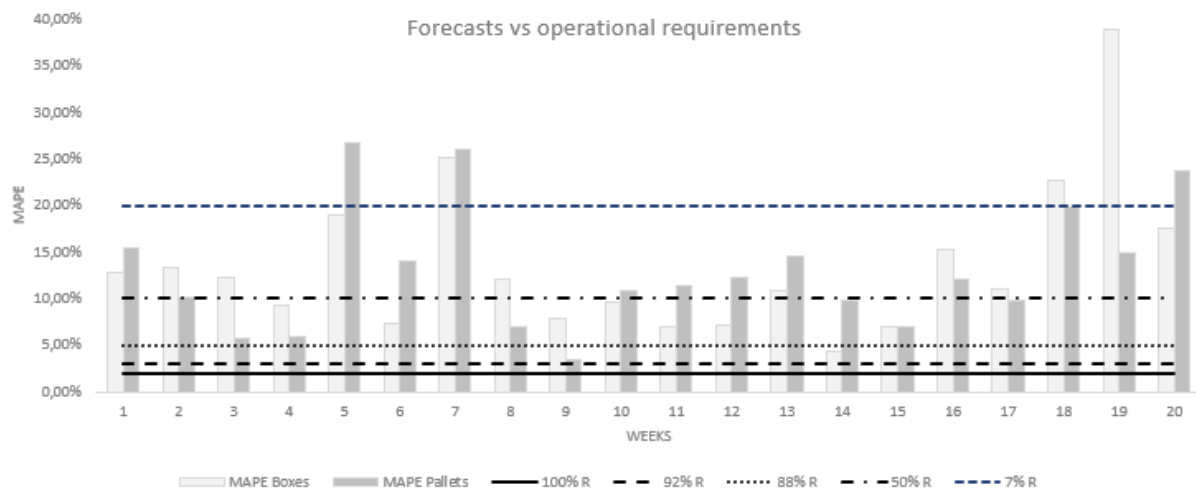


Fig 8. Forecasts compared to identified requirements

Source: own elaboration

The algorithm considered did not meet the requirements set for it by the managers working for the selected logistics operator during the testing period. The reason for this state of affairs, and at the same time directions for further considerations and improvements in this area, could be the following.

- Insufficient quality of input data for the forecast model. The operator relies on disturbed data on the size of the end customer's demand, this is due to the place that the operator occupies in the distribution network and the ineffective system of information flow between various links in the network. This problem could be solved by developing appropriate methods of cooperation and the use of modern methods related to the improvement of information flow.

- Unrealistic requirements of managers with regard to the current possibilities of predicting the size of demand and its consequences. Currently, the operator does not use any forecasting tool, and the results related to underestimating or overestimating the size of demand are not collected and analysed, and thus are not easily measurable. Perhaps the forecast results provided by the current solution would be sufficient to improve the current state of resource planning. A way to test this state of affairs could be to conduct a pilot study using the current solution and to check the results and benefits it brings in practice.

- Poorly functioning forecasting algorithm. This can be solved by implementing other forecasting algorithms into the calculations and selecting a more tailored algorithm based on their matching to the established algorithm training areas. Additionally, an option related to, e.g., searching for the appropriate time window for creating a forecast training area may be considered here [Wolny and Kmiecik 2020].

However, the usage of ARIMA models gives the opportunity to create the proper forecasting system. ARIMA models are often explored in the research [Sohrabpour et al., 2021; Chu & Zhang, 2003], even as a basis for more advanced forecasting attitudes connected, for example, with artificial neural networks [Bayraktar et al., 2007]. It seems that the proper prospect for development will also be to use an ARIMA with support of generic programming [Sohrabpour et al., 2021] or with additionally ANOVA analysis [Bayraktar et al., 2007]. The logistics operator has a strong predisposition to start with the demand forecasting [Kramarz and Kmiecik, 2022], but operators are the most frequently associated with forecasting due to the fact that operators often forecast the financial profitability of some projects [Wang et al., 2018]. Very often, operators are considered as units that forecast demand in the area of transport operations or forecasts of cross-docking activity [Grzelak et al., 2019], but it is not an implementation approach from the perspective of the usefulness of this function for the entire distribution network, and is more based on the

appropriate use of data occurring in 3PL companies. In summary, it is possible to create a forecasting tool used by a logistics operator to forecast demand for operational needs. The logistics operator itself, implementing a forecasting tool, would operate under risk conditions. Minimizing this risk would mainly consist of improving the methods that the operator would use to create forecasts and in developing the operator's analytical skills in the field of demand forecasting. However, the area to focus on is the area related to the possibility of reducing the forecasting errors that such a solution generates.

ACKNOWLEDGMENTS

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

- Alevizos, E., Artikis, A., & Paliouras, G., 2018, Wayeb: a tool for complex event forecasting. arXiv preprint arXiv, <https://arxiv.org/abs/1901.01826>
- Barlas, Y., & Gunduz, B., 2011, Demand forecasting and sharing strategies to reduce fluctuations and the bullwhip effect in supply chains. *Journal of the Operational Research Society*, 62(3), 458-473, <https://doi.org/10.1057/jors.2010.188>
- Bayraktar E. & Koh S.L., 2007, Gunasekaran, A.; Sari, K.; Tatoglu, E. The role of forecasting on bullwhip effect for E-SCM applications. *Int. J. Prod. Econ.* 2007, 113, 193–204, <https://doi.org/10.1016/j.ijpe.2007.03.024>
- Berk, L., Bertsimas, D., Weinstein, A. M., & Yan, J., 2019, Prescriptive analytics for human resource planning in the professional services industry. *European Journal of Operational Research*, 272(2), 636-641, <https://doi.org/10.1016/j.ejor.2018.06.035>
- Broberg, T., & Persson, L., 2016, Is our everyday comfort for sale? Preferences for demand management on the electricity market. *Energy Economics*, 54, 24-32, <https://doi.org/10.1016/j.eneco.2015.11.005>
- Chu, C. W., & Zhang, G. P., 2003, A comparative study of linear and nonlinear models for aggregate retail sales forecasting. *International Journal of production economics*, 86(3), 217-231, [https://doi.org/10.1016/S0925-5273\(03\)00068-9](https://doi.org/10.1016/S0925-5273(03)00068-9)
- Croxton, K. L., Lambert, D. M., García-Dastugue, S. J., & Rogers, D. S., 2002, The demand management process. *The International Journal of logistics management*, 13(2), 51-66, <https://doi.org/10.1108/09574090210806423>
- Fahrioglu, M., & Alvarado, F. L., 2001, Using utility information to calibrate customer demand management behavior models. *IEEE transactions on power systems*, 16(2), 317-322, <https://doi.org/10.1109/59.918305>
- Grzelak M., Borucka M., Buczyński Z., 2019. Forecasting the demand for transport services on the example of a selected logistic operator, *Archives of Transport* , vol.52, pp.81-93. <https://doi.org/10.5604/01.3001.0014.0210>
- Mentzer, J. T., & Thomas Jr, D. E., 2000, Customer demand planning at Lucent Technologies. *Industrial Marketing Management*, 29(1), 19-19. [https://doi.org/10.1016/S0019-8501\(99\)00108-X](https://doi.org/10.1016/S0019-8501(99)00108-X)
- Kalantari, M., Rabbani, M., & Ebadian, M., 2011, A decision support system for order acceptance/rejection in hybrid MTS/MTO production systems. *Applied Mathematical Modelling*, 35(3), 1363-1377, <https://doi.org/10.1016/j.apm.2010.09.015>
- Kim, M. S., Kim, K. W., & Park, S. S., 2012, A study on the air travel demand forecasting using time series ARIMA-intervention model. *Journal of the Korean Society for Aviation and Aeronautics*, 20(1), 66-75, <https://doi.org/10.12985/ksaa.2012.20.1.066>
- Kmiecik, M., 2021, Implementation of forecasting tool in the logistics company—case study. *Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska*, <https://doi.org/10.29119/1641-3466.2021.152.9>

- Kramarz, W., 2013, Modelowanie przepływów materiałowych w sieciowych łańcuchach dostaw: odporność sieciowego łańcucha dostaw wyrobów hutniczych. *Difin*.
- Kramarz, M., & Kmiecik, M., 2022, Quality of Forecasts as the Factor Determining the Coordination of Logistics Processes by Logistic Operator. *Sustainability*, 14(2), 1013, <https://doi.org/10.3390/su14021013>
- Martin, D., Spitzer, P., & Kühl, N., 2020, A new metric for lumpy and intermittent demand forecasts: Stock-keeping-oriented prediction error costs. *arXiv preprint*, <https://arxiv.org/abs/2004.10537> <https://doi.org/10.48550/arXiv.2004.10537>
- Morris, J. N., Sherwood, S., & Gutkin, C. E., 1988, Inst-Risk II: an approach to forecasting relative risk of future institutional placement. *Health Services Research*, 23(4), 511.
- Omar, H., Hoang, V. H., & Liu, D. R., 2016, A hybrid neural network model for sales forecasting based on ARIMA and search popularity of article titles. *Computational intelligence and neuroscience*, 2016, <https://doi.org/10.1155/2016/9656453>
- Panahifar, F., Heavey, C., Byrne, P. J., & Fazlollahtabar, H., 2015, A framework for collaborative planning, forecasting and replenishment (CPFR): state of the art. *Journal of Enterprise Information Management*, <https://doi.org/10.1108/JEIM-09-2014-0092>
- Sohrabpour, V., Oghazi, P., Toorajipour, R., & Nazarpour, A., 2021, Export sales forecasting using artificial intelligence. *Technological Forecasting and Social Change*, 163, 120480, <https://doi.org/10.1016/j.techfore.2020.120480>
- Subramanian, L., 2021, Effective demand forecasting in health supply chains: emerging trend, enablers, and blockers. *Logistics*, 5(1), 12, <https://doi.org/10.3390/logistics5010012>
- Szozda, N., & Świerczek, A., 2016, Efektywność procesu zarządzania popytem na produkty w łańcuchu dostaw. *Zeszyty Naukowe Uniwersytetu Gdańskiego. Ekonomika Transportu i Logistyka*, (58 Modelowanie procesów i systemów logistycznych, Cz. 15), 157-175.
- Świerczek, A., 2019, The effects of demand planning on the negative consequences of operational risk in supply chains. *LogForum*, 15(3), <https://doi.org/10.17270/J.LOG.2019.340>
- Wacker, J. G., & Lummus, R. R., 2002, Sales forecasting for strategic resource planning. *International Journal of Operations & Production Management*, <https://doi.org/10.1108/01443570210440519>
- Wang Ch-N., Day J-D., Nguyen T-K-L., 2018, Applying EBM and Grey forecasting to assess efficiency of third-party logistics providers, *Journal of Advanced Transportation*, vol.2108, pp.44575, <https://doi.org/10.1155/2018/1212873>
- Westcott, R., 2004, A scenario approach to demand forecasting. *Water Science and Technology: Water Supply*, 4(3), 45-56, <https://doi.org/10.2166/ws.2004.0042>
- Williams, B. D., & Waller, M. A., 2011, Top-down versus bottom-up demand forecasts: the value of shared point-of-sale data in the retail supply chain. *Journal of Business Logistics*, 32(1), 17-26, <https://doi.org/10.1111/j.2158-1592.2011.01002.x>
- Wolny, M., & Kmiecik, M., 2020, Forecasting demand for products in distribution networks using R software. *Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska*, <https://doi.org/10.29119/1641-3466.2020.142.8>

Mariusz Kmiecik ORCID ID: <https://orcid.org/0000-0003-2015-1132>
Silesian University of Technology
Zabrze, **Poland**
e-mail: mariusz.kmiecik@polsl.pl

Maciej Wolny ORCID ID: <https://orcid.org/0000-0002-8872-7794>
Silesian University of Technology
Zabrze, **Poland**
e-mail: maciej.wolny@polsl.pl