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ORIGINAL PAPER

SUPPORTING OF MANUFACTURING SYSTEM BASED ON DEMAND FORECASTING TOOL

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ABSTRACT. Background: Enterprises' decision-making could be facilitated by properly creating or choosing and implementing demand forecasting systems. Currently, there are more and more advanced forecasting algorithms based on sophisticated technologies such as artificial neural networks and machine learning. The following research paper focuses on a case study of an automotive manufacturer. The main research aim is to propose the proper demand forecasting tool and show the prospects for implementing the mentioned solution.

Methods: The research paper contains the statistical analysis of a chosen time series referring to the demanded quantity of the manufactured products. To create forecasts, models based on the following forecasting algorithms were created: ARIMA, ELM (Extreme Learning Machine), and NNAR (Neural Network Autoregressive). All algorithms are based on the R programming language. All algorithms are run in the same time series where the training and testing periods were established.

Results: According to the forecasts ex-post errors and FVA (forecasts value-added) analysis, the best fitting algorithm is the algorithm based on ELM. It yields the most accurate predictions. All other models fail to add value to the forecast. Specifically, the ARIMA models damage the forecast dramatically. Such significant magnitudes of negative FVA values indicate that choosing not to forecast and plan based on the sales of the same period of the previous year is a better choice. However, in the case of the ELM model, the forecasts can be worth the time, finance, and human resources put into preparing them.

Conclusion: The increased accuracy of ELM forecasts can contribute to optimizing the process of reaching consensus forecasts. While unconstrained statistical forecasts tend to be overridden, not only to produce constrained forecasts incorporating various variables such as calendar events, promotional activities, supply capacity, and operational abilities, they are also overridden by planners to reflect their foreseeing of demand. The proposed solution could also be easily implemented in the resource planning process to improve it. The proposition of the resource planning process supported by the proposed forecasting system is also shown in the following paper using a BPMN 2.0 (Business Process Modelling Notation 2.0) map.

Keywords: demand forecasting, R Studio, ARIMA model, Neural Network model, Machine learning model, manufacturing system

THEORETICAL BACKGROUND

Forecasting is the process of analyzing and utilizing available information in the form of historical data and knowledge of the future to predict potential future events. It is crucial to distinguish forecasting from prediction, forecasting is a type of prediction, and it bases the future outcomes on temporal recorded data. In contrast, the prediction has three sub-disciplines. They are the prediction of the future, which attempts to predict the state of the future; prediction to the time of reference, which is an attempt to predict what is happening at the time of the making prediction, and prediction to the past, which attempts to predict the occurrence of the past. In essence, every forecast is a type of future prediction; however, not all future predictions are forecasts, as forecasts focus on not only a future occurrence but also the time of the occurrence. While some future predictions bluntly predict an occurrence without any insight into the timing of the occurrence or other parameters such as errors and confidence intervals. Furthermore,

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forecasting is a prediction based on quantitative or qualitative methodologies, and in the case of quantitative forecasts, the models have measurable errors. In comparison, a prediction might be subjective and based solely on gut feeling. In forecasting literature, generally, forecasts refer to the process of predicting future values, while predictions refer to the values themselves [Gische et al., 2020].

A successful demand forecast facilitates decision-making and improves final decisions regarding the scheduling of production, transportation, and personnel, and provides a guide to long-term strategic planning. [Hyndman and Athanasopoulos, 2018] In order to forecast demand accurately, an enterprise needs to have sufficient historical data to capture a bigger picture of the characteristics of demand. Despite the fact that the availability of sufficient data is the very first requirement of demand forecasting, the value needs to be extracted from the time-series data through the selection and use of compatible forecasting methods that are capable of taking trends, seasonality, and randomness of the data into account. Following the method selection, the parameter(s) of the method needs to be tweaked to enhance the model in order for it to mimic the behavior of the data more accurately and precisely. Additionally, demand prediction depends on the comprehension of contributive factors such as volatility and uncertainties involved. Demand volatility is unpredictability and rapid changes in demand.

Forecasting is considered as one of the risk categories in material flows [Szozda and Werbińska-Wojciechowska, 2013] also in production. Mentioned risk factors are imprecision, seasonality, product differentiation, short product life cycle, insufficient customer database, and information deviation. Demand fluctuations could imply supply management problems and create a tendency to keep excessive stocks as a buffer to production systems. Using flexible and precise forecasting procedures gives possibilities to gain good results even in capricious markets where the ordering practice of middleman distorts the demand of ended participants [Vokhmyanina et al., 2018]. The main features of demand on flowing goods are [Chandra and Grabis, 2007; Malladi and Sowlati, 2018]: the size of orders (it is the average quantity of orders); demand predictability (defines the error in forecasting); demand variability (it is the relation between demand pattern and average demand); market size (it is a rate of penetration for the specific products categories) and domestic market strength (in comparison to the global demand of a company).

In consideration of the meaning of forecasting in companies' activities, special attention should be paid to incorrectly created forecasts. Demand revaluation could cause for example high costs of excessive stocks and high marketing costs to get rid of them. Underestimation, on the other hand, could cause for example lost sales, lost reputation, and underestimated levels of sales tasks [Krzyżniak, 2017]. Forecasting has a special meaning especially in the context of manufacturing because the manufacturer forecasts usually influence whole supply chains [Mesjasz-Lech, 2011]. Through using proper forecasting methods as a part of demand planning there is a possibility of reducing the bullwhip effect [Dujak et al, 2019; Vokhmuanina et al, 2018] and also have a strong influence on the whole decision-making process [Czwajda et al, 2019].

Forecasts are created by strategists to identify business threats and spot emerging opportunities in the market [David, 2011] and for the purpose of predicting the future demand in order to plan ahead to meet demand and reduce risks arising from uncertainty. Through accurate forecasts and planning, enterprises can reduce working capital and other associated costs by manufacturing the optimum quantity of products and stocking the optimum amount at the right location at the right time. The accuracy of forecasts directly affects those variables and corrective action tends to be expensive and time-consuming in case of higher lead times. Failure to forecast can result in the failure of a business. Demand forecasting, along with demand planning constitute demand management. Demand forecasting and management form the foundation for all planning processes. Demand management is also one of those areas that companies continue to struggle with. Regardless of how good the demand management of an enterprise is, there still appears to be room for potential improvement [Chase, 2016]. Being able to meet demand optimally, leads to cost reduction, increasing profit, customer retention, and meeting corporate social responsibility expectations. The high availability of computers and their increased capabilities have facilitated the implementation of mathematical models for forecasting [Hughes and Morgan, 1967; Niazkar et al., 2020]. Furthermore, Computers have facilitated forecasting through data aggregation and visualization. Forecasting without computers takes dramatically longer, might be prone to higher error, and in some cases, it is impossible such as in using artificial neural networks. Forecasting methods are vast in quantity and specific; different behaviors of data might be grasped by different methods. Quantitative forecasting can be automated, for instance, the Box-Jenkins model, Autoregressive Integrated Moving Average (ARIMA), which can be automated in many forecasting tools and software.

Automated forecasting models are able to achieve optimal results as they are not based on human trial and error, rather than following a programmed sequence of action; however, the level of freedom they offer is significantly low, for instance, according to Hyndman, auto.arima() in R sets the AIC of some models to Inf, despite the real AIC of that model not being infinity, when the same model is rebuilt in the normal arima() function, it will have a defined AIC value. The reason that auto.arima() sets the AIC to infinity is to avoid it from being chosen based on that criterion as it does not meet other criteria such as having roots near the unit circle, which essentially means not being stationary. Another limitation of automated forecasting tools is that despite being statistically sounder, their results might not always be intuitive, for instance, in business analysis, it is necessary to check the findings of automated model selections, assess them and modify them if necessary.

More evolved and advanced forecasting models include Artificial Neural Networks (ANN), which rely on machine learning for time-series modeling. An ANN is typically composed of three types of layers, input layer, hidden layer, and output layer, each layer has neurons, essentially simplified neurons. In a single layer ANN, there is only an output layer, and the inputs are directly fed into the output neurons. while multilayer ANN is composed of all three types of layers, and the neurons can have multiple connections across the neurons of the other layers. In terms of the direction of outputs, ANN can be feedforward-based or recurrent-based. In a feedforward-based ANN the outputs of neurons can only be input for the neurons of an upper layer, whereas, in recurrent ANN, the output of neurons can also be fed back into the same neuron or neurons of a lower layer. Prior to achieving satisfactory results from an ANN, it has to be trained, which determines correct weights and biases. In forecasting, a time series is the input of the ANN, and forecasted values are the outputs. The input (time-series) has to be divided into two subsets, a training subset and a testing subset, the former one is used for training the neural network to assign weights that yield a lower overall error, while the latter one is used for measuring and assessing the abilities of the ANN [Zhang et al., 1998; Khandelwal et al., 2015]. Thus, the evolution of forecasting has a wide horizon, and quantitative forecasting can be as simple as the Naïve method, or as complex as artificial neural networks.

A limitation of forecasting arises from the need for increasing the granularity of forecasts for short-term planning. The basic issue of short-term prediction is the selection of the optimum time granularity, which directly affects the accuracy of forecasts [Li et al., 2019]. While some enterprises can manage demand on long-term low granular forecasts due to longer lead times, others cannot. For certain industries, low granular forecasts cannot be used for planning, such as in those industries where product lead times and shelf lives tend to be shorter and risks of spoilage or obsolescence could be high, such as in the fast-moving consumer goods (FMCG), technology, and fashion industries. In such industries daily or even weekly forecasts are more valuable than monthly forecasts. AI-based demand forecasting solutions surpass traditional statistical forecasting methods in accuracy for short-term forecasting, as a result reducing safety stock and stockouts at points of sale, thus, increasing profitability [Tarallo et al., 2019].

Another limitation of forecasting is its tedious process of carrying out. One workaround is aggregate forecasting, also known as top-down (TD) forecasting. In some industries, aggregating forecasts by product groups, divisions, and subsegments is possible due to the similarity of the products and a nearly constant historical relativity. Aggregate forecasts are developed for all products at once and through individual historical relative demand frequency, the demand of each individual product is allocated. [Dangerfield et al., 1992] Forecasting the demand of a group of products yields more accurate results than forecasting the demand of an individual product within the group [Narasimhan et al., 2007] this, is due to the fact that summing the individual forecasts up results in a large variance, hence, forecasting the demand of all products at once is better [Fogarty et al., 1994]. However, when the aggregate forecast is allocated to individual products, the accuracy is less compared to the accuracy of disaggregate forecasts with individual models [Dangerfield et al., 1988]. This is due to the top-down approach having many disadvantages, among those is the substantial information loss resulting from the aggregation of data [Orcutt et al., 1968]. The application of the top-down approach can be in the dairy industry, a farm can use an aggregate forecast of dairy products to plan future milk production, then based on historical relativity, the demand for individual products such as homogenized milk, yoghurt, and others can be allocated.

The main research problem of the following research paper is the comparative analysis of the accuracy of machine learning based forecasting models and traditional statistical forecasting models in the example of the selected production enterprise. To create and compare forecasting solutions were chosen the algorithms from the R programming environment were. R is a programming language for statistical analysis of the data which is chosen willingly in universities research as presented in Figure 1.

Tested algorithms in the conditions of machine learning will be ELM, MLP, and NNAR algorithms from the R programming environment. On the opposite side, there will be ARIMA and an automated ARIMA algorithm also calculated in R.

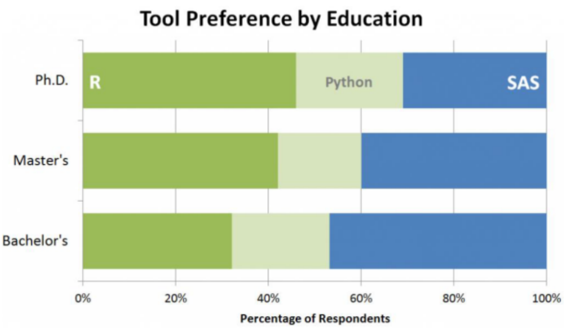

Fig 1. Preferences of predictive analytics tools across different levels of education

source: [Burtch, 2016]

The forecast package contains functions for manual and automated forecasting methods, and the artificial neural network tool in this package is Neural Network Autoregression (NNAR) which puts to work a single hidden layer feedforward neural network to forecast univariate time-series (figure 2). It is called through the function nnetar(). The NNAR model uses the lags of the time-series as inputs to the neural network, and it is important to note that it does not restrict its parameters to ensure stationarity. This artificial neural network uses a backpropagation algorithm to update the weights to obtain the minimum sum of squared errors. Artificial neural network methods are proven to give better results when there is volatility in demand [Mahbub and Paul, 2013].

Extreme Learning Machines (ELM) is a function from the package nnfor which serves as an automatic, semi-automatic, or fully manual modeling of artificial neural networks for time-series forecasting. What sets ELM aside is that it can only have one hidden layer, and furthermore, the learning algorithm, which was first proposed by G, -B Huang, et al. It sets out to solve one limitation of artificial neural networks, which is high time consumption in the training process. Instead of iterated learning through backpropagation, ELM uses simple inverse operation to find the output weights analytically. [Huang, et al, 2004; Liu et al., 2018].

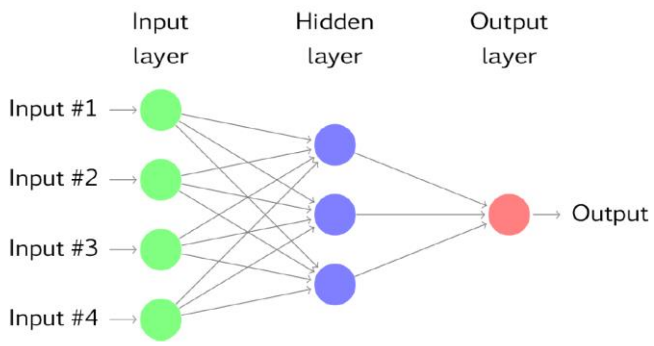

Fig. 2. A sample ANN

source: [Hyndman and Athanasopoulos, 2018]

Another function from the nnfor package, MLP, fits a multilayer perceptron neural network to a time-series for forecasting. MLP function creates a multilayer perceptron and trains it. MLPs are fully connected feedforward networks and probably the most common network architecture in use. Training is usually performed by error backpropagation or a related procedure [Rdocumentation, 2021].

AI is increasingly adopted as a problem-solving tool in business [Davenport and Ronanki 2018; Gunasekaran et al. 2017; Lee 2018; Phan et al. 2017] and the unsurpassed learning capabilities of AI can aid demand management in emergency situations as well. The COVID-19 pandemic forced many enterprises to transform and remodel their supply chains [Ivanov, 2020]. Artificial intelligence as a solution addresses issues associated with supply chain resilience and offers potential approaches to promote long-term sustainability [Modgil et al., 2021]. AI encompasses big data, machine learning, and deep learning technologies [Gupta et al., 2021; Wamba et al., 2020; Dwivedi et al., 2019]. It can empower the procurement strategy of the organization through automation of contractual agreements with suppliers and avoid redundancy of a supply chain through improved decision-making capabilities. [Baryannis et al., 2019; Dubey et al., 2020]. Furthermore, AI is capable of developing genetic algorithms and agent-based systems to facilitate demand planning, inventory planning, and network design in conjunction with supplier systems [Muniz et al., 2020]. While AI can have a broad range of applications in demand management, specifically for demand forecasting, AI offers demand sensing, which is the utilization of upstream data within a value chain to generate a more accurate unconstrained demand forecast [Chase, 2009]. The COVID-19 pandemic caused many manufacturing plants to halt production due to supply chain disruptions. The surge of demand following the low demand for many products lead to a bullwhip effect. A potential solution could be drawing insights from data directly related to the cause of the event or the state of the event. In other words, to incorporate historical sales data with other correlated data.

Other than forecasting demand for managerial and operational planning and controlling, accurate demand planning can be used for strategic planning. For instance, existing knowledge can be devalued by turbulence, also, ongoing turbulence may devalue investments in exploration aimed at the generation of new knowledge [Posen, et. al, 2012], and high accuracy AI-powered demand forecasting could predict the frequency of turbulence, thus, justifying strategic decisions such as exploration or exploitation.

Currently, more and more entities are taking advantage of contemporary technological achievements. It is popular especially in the activity of automotive enterprises which are the basic enterprises involved in the Industry 4.0 development. Nowadays, automotive enterprises are striving with the issue of demand planning necessity and Big Data common occurring in their environment. All the mentioned issues started the considerations of supporting the manufacturing process by highly technological advanced demand forecasting tool.

MANUFACTURER AND PRODUCT DESCRIPTION

The historical data used in the empirical part of this thesis is the sales of the lineup of pickup trucks manufactured and marketed by an American automotive manufacturer. The mission statement of the manufacturer shows that it wants to leave its fingerprint everywhere and provide people with its vehicles at affordable prices to make improvements in people's lives. The company has a vision of rapid development for their products to provide vehicles with high-end technology to the whole globe, and it wants to gain the trust of customer loyalty. The manufacturer serves the market across the globe.

The manufacturing strategy of the company is based on the flexibility strategy. It abandoned the dedicated assembly lines, which were capable of manufacturing only one model, in favor of flexible plants. The flexible plants have reprogrammable body tooling and a common final assembly line that can seamlessly shift the production of different models. The pickup truck lineup, which is the subject of this research, comprises eight distinct models, and the lead time for their production is in the range of 16 to 26 weeks, depending on the model. The relatively long lead time of roughly a half-year-long requires resilient demand management to avoid underproduction and overproduction.

Overproduction has been a major theme in the American automotive industry. Many states prohibit manufacturers from selling directly to end-users. Thus, the dealers are not owned by the manufacturer. To minimize the losses resulting from overproduction, the manufacturers force the dealers to take more and more cars, this activity is known as "channel stuffing," and it causes substantial financial loss for the dealers, yet the manufacturers regard this as revenue even though the cars are parked in the dealership without real demand from an end-user. A cause of overproduction is associated with manufacturing more units to spread out the fixed costs, which is essentially an outcome of overcapacity and its utilization. As a result, the supply of the products is greater than the market demand. Therefore, in demand forecasting, the first step to take is to make sure the data truly represents the demand, if not so, regardless of how efficient the forecasting model is, the forecasted values cannot capture the true future demand.

The manufacturer has faced limitations in production and supply. After the dramatic decrease of demand in the fourth quartile of 2019 and the first quartile of 2020 due to the COVID-19 pandemic, the sales in 2021 are recovering back to their normal level, and the demand is high. Meanwhile, the limited supply of semiconductor chips at the beginning of February 2021 pushed the manufacturer to lay off shifts at their truck assembly plants. Thus, unable to match supply and demand, damaging the earnings.

The product, essentially a lineup of trucks, is marketed using a product differentiation strategy along with a low-cost leadership strategy; thus, the company manufactures products that are different from those of its competitors at lower costs. The company uses Caterpillar logistics services and SAP as enterprise resource planning (ERP) software, as well as SAS for data analysis. SAS is used for customer relationship management (CRM) as it has access to its customer relationship database, and it can produce predictive models. The historical data available for analysis and forecasting spans from January 2005 to January 2021, resulting in a total of 193 monthly observations. While this monthly data is of the whole lineup, The manufacturer needs to adjust the forecasts according to the market share of each eight individual models. Failure to accurately estimate the market shares of the individual models results in adding no value from the forecasts derived from these data.

The visualizations of the historical sales data and decomposed elements of the time series show that the sales data exhibits seasonality, and there is no persistent trend over the whole span of the historical data; however, the sales experience long periods of rising and fall. There is an overall negative trend from 2005 to 2009 and an overall positive trend from 2009 on. The seasonal plots suggest that the sales are generally peaking in December and troughing in January.

The lineup has experienced abrupt changes and deviations in sales which cannot be explained by the trend and seasonality, thus referred to as outliers. After running an in-depth outlier detection, the following outliers were found:

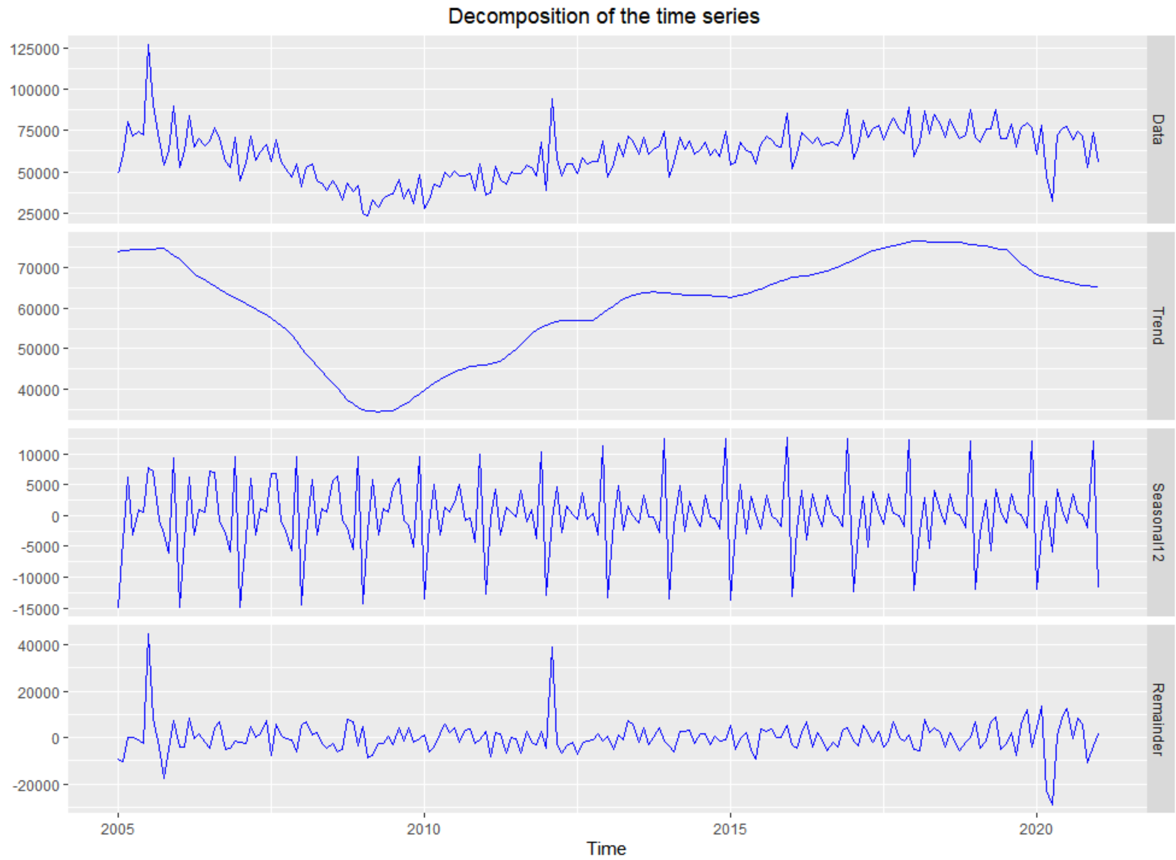

Fig. 3. Decomposition of the time series.

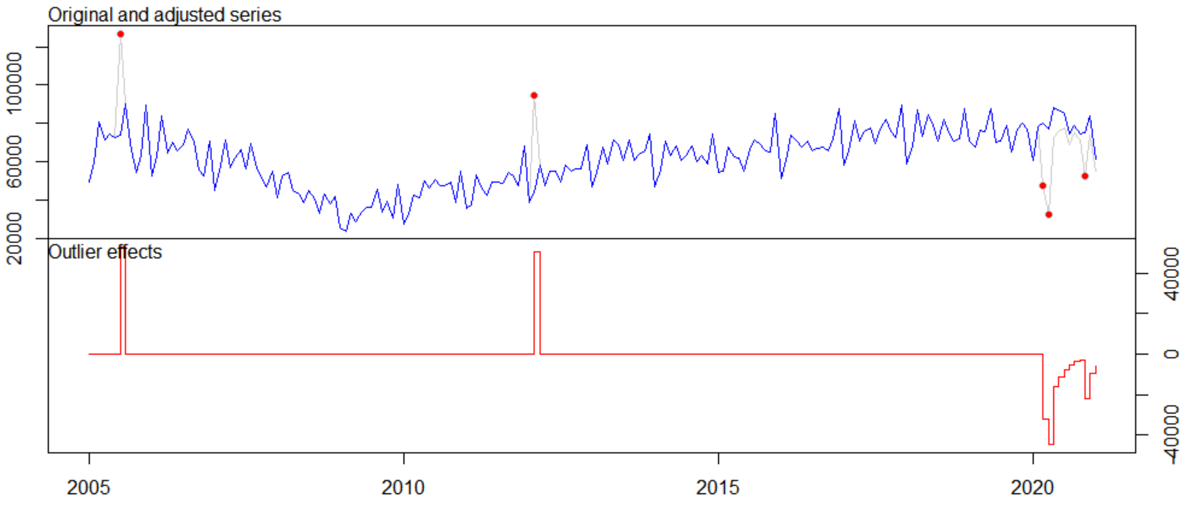

Fig. 4. Outliers of the time series and their effects.

Table 1. Outliers and their specifications.

Type	Index	Date	Coefficient	T-stat
AO	7	07.2005	52897.90436	11.24752354
AO	86	02.2012	50630.10018	13.06091663
TC	183	03.2020	-32335.06991	-6.705837541
AO	184	04.2020	-22138.05043	-4.833218304
IO	191	11.2020	-20358.05615	-3.516511451

The first outlier, located at index 7, is of type additive, and it is the result of sale promotion. While the second outlier at index 86 is also additive and it is due to the success in achieving high sales figures in 2012. The last three outliers are all negative and are caused by the supply chain disruptions and decrease in demand due to the COVID-19 pandemic-related events.

PROPOSED DEMAND FORECASTING MODEL

The studied models consist of a manual and an automated autoregressive integrated moving average (ARIMA), an extreme learning machine (ELM), a multilayer perceptron (MLP), and a neural network autoregressive (NNAR), of which the last three are machine learning based. The procedure to test their performance is divided into four main steps—namely, model studying, training, forecasting, and analysis of the results. In the first step, the models are studied both in terms of their mathematical algorithm, as well as the functioning of the models in the certain tool used, i.e., R. By studying algorithms, one can understand the roles and effects of the variables in the algorithms and studying the function and operation of the models of the tool helps in setting the models for the best possible results. In the second step, the time series is split into two new sets, the training, and the test set, at the ratio of 80:20. Then, the optimal inputs to be passed into the functions are determined through gaining intuition from the time series, such as its autocorrelation and partial autocorrelation function plots, and then they are fine-tuned through systematic experimentation. The algorithms of the artificial neural network (ANN) based models involve starting with random weights, thus, prior to systematic experimentation, the usage of the same randomly generated weights is ensured. Before proceeding to the third step, the models are tested for the maximum achievable accuracy. While for the simpler forecasting methods like the naive method, weighted moving average, and winter's method, the best model is determined through calculating the ex-post errors and choosing the minimum one. This model selection criterion is not a good measure of the performance of the models in predicting the future; in fact, the forecasting methods used in this paper achieve negligible ex-post errors, overfitting the data, which is best to be avoided in forecasting demand. Therefore, instead of relying on hyperparameter tuning to minimize the in-sample ex-post errors, the hyperparameters are tuned to build models which have the best residuals, neither overfitting nor underfitting, but capturing the essence of the time series. In the third step, the models are run, and the in-sample and out-of-sample ex-post errors are recorded. In the fourth step, the forecasts are compared based on their accuracy as well as a forecast value added (FVA) analysis.

The forecasting procedure starts with importing the data into Rstudio and converting it into a time-series format. The time series is then split into the training and test set. The training set is checked for skewness, and the optimal lambda (λ) value of Box-Cox transformation is found if it needs power transformation.

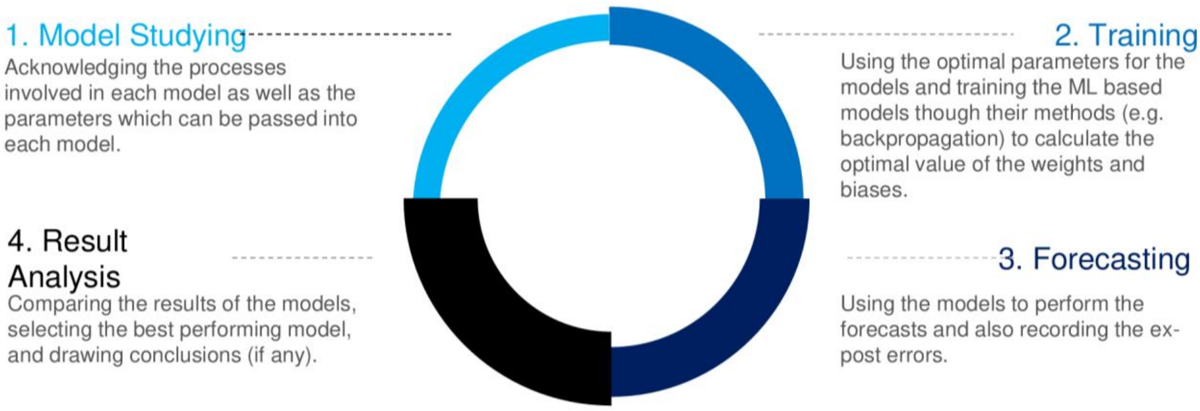

Fig. 5. Methods of the research.

After that, augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are performed to check for stationarity of the training set, if not stationary, the optimal number of differencing is found to make it stationary. Then the training set along with the hyperparameters are passed into the forecasting model. After forecasting, a Ljung-Box test is performed on the residuals of the forecast to check for any autocorrelation left, if there are any, the hyperparameters of the model are tuned to eliminate the autocorrelation. Next, the out-of-sample forecasting ex-post errors, namely, MAPE and RMSE, are calculated from the actual values (i.e., the test set) and the forecast values. Finally, the forecast value added (FVA) is calculated using the ex-post errors of a seasonal naive forecast. Among the artificial neural networks used, the extreme learning machine (ELM) and the multilayer perceptron (MLP) functions do not natively support Box-Cox transformation, thus as a workaround, the models are trained on a transformed version of the training set, and after being trained, the models forecast the non-transformed training set without retraining the networks.

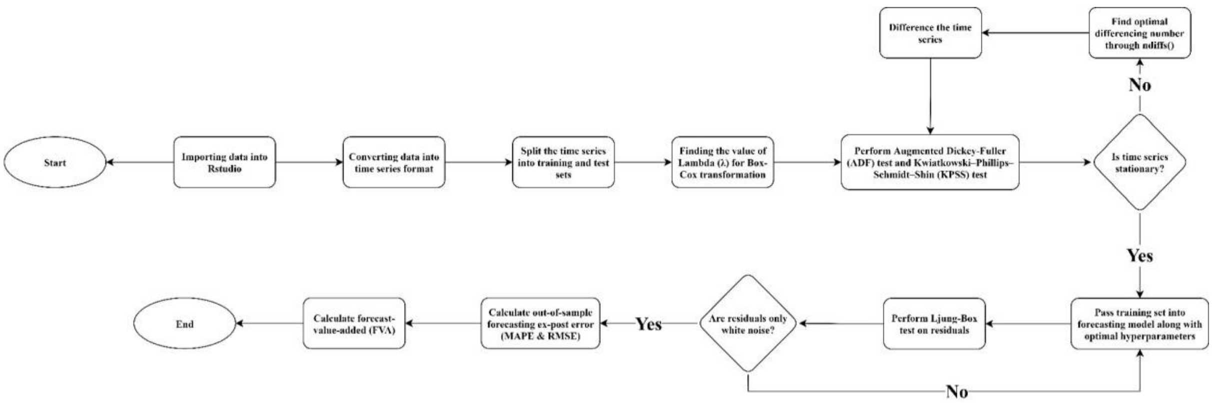

Fig. 6. Forecasting procedure.

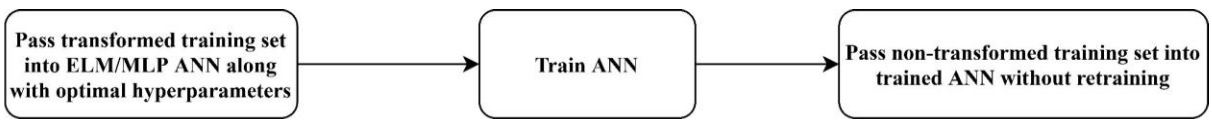

Fig. 7. Training procedure of ELM and MLP neural networks

The presented method offers the opportunity to the manufacturer to improve demand planning by using advanced demand forecasting algorithms, but it also has some limitations. The method and proposed algorithms with data analysis fit only the products with sales history. Also, the training period is stated in the same level of time series, in every calculation, the same percentage part of historical data is used for algorithm training.

RESULTS & CONCLUSION

The accuracy of the forecasting models is calculated in terms of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). While the former is scaled and measured in terms of actual units sold, the latter is a percentage that is more comprehensible. While both metrics describe the ex-post errors of the forecasts, they are not necessarily proportional, and they can be sensitive to different situations.

The ex-post errors of the models are as the following:

Table 2. Accuracy of the models.

Model	MAPE	RMSE
ARIMA	22.18%	16750.82
Auto RIMA	22.63%	17100.36
ELM	11.71%	9752.33
MLP	13.85%	10310.30
NNAR	13.98%	10553.63

The ARIMA models were outperformed by the artificial neural networks. While the ARIMA and automatic ARIMA models had a MAPE of 22.18% and 22.63%, respectively, the MLP and NNAR models achieved a MAPE of 13.85% and 13.98%, respectively. The manual ARIMA model performed better than the automatic one. The forecasts of the ELM model resulted in an outstanding MAPE of only 11.71%, almost half the MAPE of the ARIMA models.While in the particular industry of automotive manufacturing, the lead times tend to be long, it is worth looking at the short-term forecasting performance of the models. While both MLP and NNAR models outperformed the two ARIMA models in the long run, taking only the first five forecasted periods into account, in the short run, it was quite the opposite as the ex-post errors of the MLP model were unstable, fluctuating between greater extrema. While the NNAR model performed better than the MLP model, it did not manage to perform as well as the ARIMA models. Also, unlike the long-term forecast, in the short-term forecast, the automatic ARIMA performed marginally better than the manual ARIMA. The ELM model had the most accurate short-term forecast, and the ex-post errors were increasing without fluctuations, almost linearly. While comparing the ex-post errors of different forecasts is a method of determining which is superior, it cannot alone justify the value it adds, it is rather a relative measurement. For that purpose, the Forecast Value Added (FVA) analysis is performed to calculate the value each model's forecast adds. An FVA analysis compares the accuracy of forecasts to the accuracy of a basic forecast from either the naive method or the seasonal naive method, since the sales of the subject of this study are highly seasonal, the seasonal naive method is used as a benchmark. While an FVA analysis can incorporate judgmental forecasts, such as an analyst's override, this FVA analysis does not contain judgmental forecasts, and its sole purpose is to examine the added value from the forecasts of the individual models.

According to the FVA analysis, the only model capable of adding value to the forecast is the ELM model, as its forecast has a MAPE value that is less than the MAPE of the seasonal naive forecast. Meanwhile, all other models fail to add any value to the forecast, specifically, the ARIMA models damage the forecast dramatically. Such great magnitude negative FVA values indicate that choosing not to forecast and planning based on the sales of the same period of the previous year is a better choice. However, in the case of the ELM model, the forecasts can be worth the time, finance, and human resources put into preparing them.

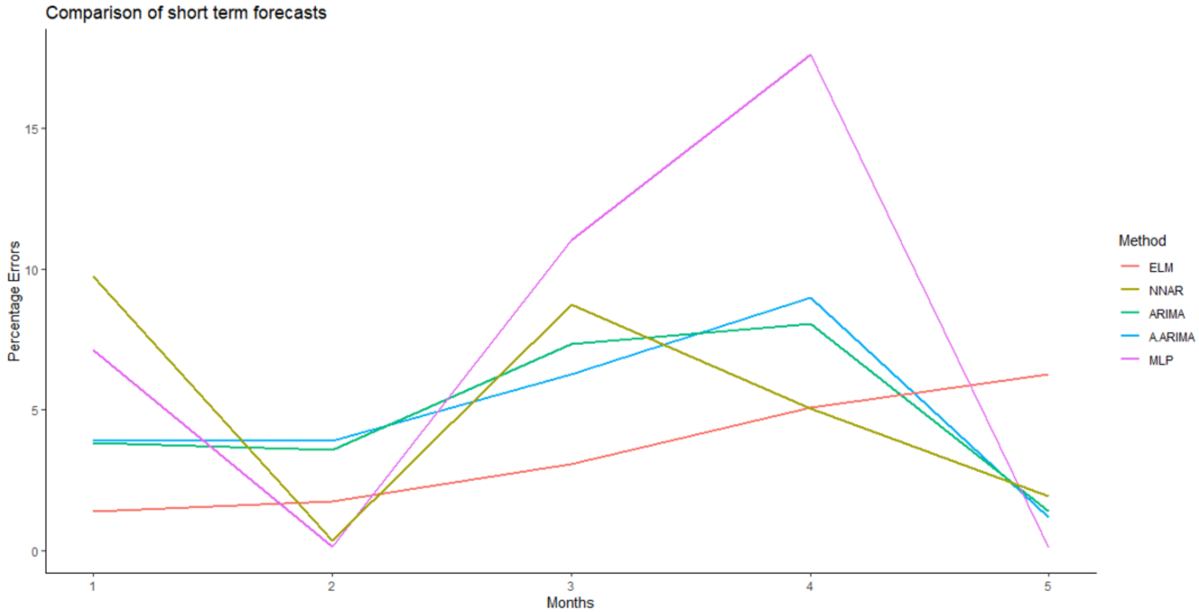

Fig. 8. Short-term forecast accuracy comparison.

Table 3. Percentage errors of the short-term forecasts.

	ARIMA PE	A. ARIMA PE	ELM PE	MLP PE	NNAR PE
1	3.92%	3.83%	1.37%	7.13%	9.74%
2	3.89%	3.56%	1.73%	0.13%	0.34%
3	6.25%	7.35%	3.08%	11.04%	8.72%
4	8.98%	8.05%	5.06%	17.63%	5.03%
5	1.19%	1.39%	6.26%	0.08%	1.93%
MAPE	4.85%	4.84%	3.50%	7.20%	5.15%

Table 4. Results of the FVA analysis.

Model	MAPE	RMSE
S. Naive	13.06%	-
ARIMA	22.18%	- 9.12%
Auto ARIMA	22.63%	-9.57%
ELM	11.71%	+1.35%
MLP	13.85%	-0.80%
NNAR	13.98%	-0.93%

The increased accuracy of ELM forecasts can contribute to optimizing the process of reaching consensus forecasts. While unconstrained statistical forecasts tend to be overridden not only to produce constrained forecasts incorporating various variables such as calendar events, promotional activities, supply capacity, and operational abilities, they are also overridden by planners to reflect their foreseeing of demand. The increased accuracy reduces the need for overriding, thus cutting on the planning time as well as the management costs. As the ELM model can predict both the far and near future of demand more accurately, it can reduce inventory costs and working capital through better optimization of inventory such as safety stock management. Furthermore, the planning horizon can be shortened as an increase of accuracy allows increasing the granularity of the forecasts without reducing the accuracy to an unacceptable level. Lastly, the benefits of the more accurate ELM forecasts result in less uncertainty and better risk management. The discussed benefits are the potential outcomes of switching to or adopting a more accurate forecasting method on its own, like the ELM network. However, the machine learning based forecasting models can be furthermore developed to meet the forecasting and planning requirements of different enterprises across different industries. What could be valuable, the analysis shows that one of the popular forecasting methods based on ARIMA has relatively low accuracy. Using machine learning or neural network based methods could bring the opportunity of preparing better demand plans, reduce the bullwhip effect in the distribution networks and also create the possibility of reducing the fluctuations and disruptions in a production system.

The proposed tool could be used, after a few modifications, to support the manufacturing system in the push strategy. The main modification will focus on increasing the automation level of the proposed solution and on integrating with the information systems of the manufacturer. Additionally, it could distinguish the data connected with sales done in push and pull systems. Using algorithms based on neural networks and machine learning gives the opportunity of finding some connections and correlations between these two kinds of data which could support the forecasting activity. Properly created and automated forecasting systems could also support the manufacturer in realizing their strategy connected with Industry 4.0. As a first step, the authors proposed to test the forecasting system as a tool for supporting manufacturing resource planning (figure 9).

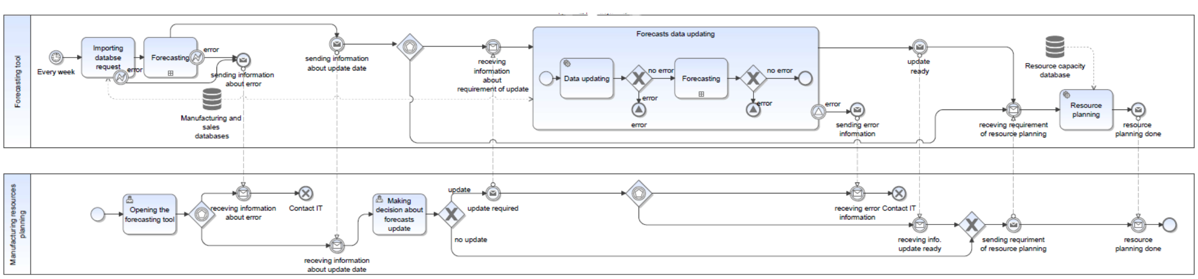

Fig. 9. Usage a demand forecasting tool for resource planning automation.

The proposed solution assumes the integration of the mentioned forecasting algorithm with databases of manufacturers. These databases consist of data connected with manufacturing, sales quantity, and capacity of particular resources. Resource planners could choose between the faster way, which is based on generated forecasts, or choose the option of updating the forecasts and sending the information of updating requirements to possess the current data from databases. Forecasts will be calculated automatically once per week with a one-month horizon. After forecasts calculation or forecasts data updating and calculation, there is automatic resource planning needed to the future values of sales predicted by the proposed algorithm.

Besides this solution, there is also a prospect for using the proposed tool to improve the level of stocks in the distribution network and to receive information about disruptions in advance. So, the proposed tool gives a lot of opportunities to improve the manufacturing system. There is also a possibility to improve the algorithms based on machine learning and neural networks by adding additional layers and trying to possess more data from the enterprise environment. The authors are also aware of the weaknesses of the proposed solution in the current state. For now, there is no possibility to use a different source data and the solution is strictly dependent on input data. Besides this, there is also a necessity of improving the collaboration between different nodes in the distribution network and supply chain, and the inclusion of the suppliers and retailers in the collaborative forecasts. These areas seem to be solvable before proper analysis which gives the opportunity to develop the following research.

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