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DEMAND FORECASTING: AI-BASED, STATISTICAL AND HYBRID MODELS VS PRACTICE-BASED MODELS - THE CASE OF SMES AND LARGE ENTERPRISES

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ABSTRACT. Demand forecasting is one of the biggest challenges of post-pandemic logistics. It appears that logistics management based on demand prediction can be a suitable alternative to the just-in-time concept. This study aims to identify the effectiveness of AI-based and statistical forecasting models versus practice-based models for SMEs and large enterprises in practice. The study compares the effectiveness of the practice-based Prophet model with the statistical forecasting models, models based on artificial intelligence, and hybrid models developed in the academic environment. Since most of the hybrid models, and the ones based on artificial intelligence, were developed within the last ten years, the study also answers the question of whether the new models have better accuracy than the older ones. The models are evaluated using a multicriteria approach with different weight settings for SMEs and large enterprises. The results show that the Prophet model has higher accuracy than the other models on most time series. At the same time, the Prophet model is slightly less computationally demanding than hybrid models and models based on artificial neural networks. On the other hand, the results of the multicriteria evaluation show that while statistical methods are more suitable for SMEs, the prophet forecasting method is very effective in the case of large enterprises with sufficient computing power and trained predictive analysts.

JEL Classification: M21, M15, C53

Keywords: demand forecasting, prophet, SME, enterprise, statistical model, artificial intelligence, hybrid model

Introduction

Demand forecasting is one of the biggest challenges of post-pandemic logistics. The pandemic has showed that the promoted just-in-time concept is not always the most suitable supply alternative. However, the existence of novel technologies has provided many techniques and methods for their users (Ključnikov et al., 2020a; Ključnikov et al., 2020b). As a result, supply-based on-demand forecasting is emerging as a possible future. Such new concepts as

Demand-Driven Adaptive Enterprise (Ptak, 2018) are proving to be functional models for the future of logistics. However, as Gya (2020) points out, enterprises face new logistics-related challenges and are forced to emphasize demand forecasting as an integral part of logistics.

This study aims to identify the effectiveness of AI-based and statistical forecasting models versus practice-based models for SMEs and large enterprises as forecasting models developed in practice (Sobczak, 2022). The study questions whether the ability of models created in practice will have the same accuracy as academia-created models when using the same dataset. Since most of the hybrid models, and the ones based on artificial intelligence, were developed within the last ten years, the study also answers the question of whether the new models have better accuracy than the older ones. We assume that newer methods (developed in the last five years) are more accurate than the older ones. Since different forecasting methods have different computing power and human resources requirements, this study also questions whether there are effective options among forecasting models available for resource-constrained SMEs when compared to larger enterprises.

As already mentioned by previous studies, SMEs have lower economic power (Metzker et al., 2021a), lower amount financial resources and assets (Civelek et al., 2020; Kliuchnikava, 2022; Rashed & Ghoniem, 2022), lower number of high quality workers (Hazudin et al., 2022; Siregar et al., 2022), more fragile structure (Civelek & Krajčík, 2022; Dvorsky et al., 2021) that cause them facing with more financial (Civelek et al., 2021; Ključnikov et al., 2021) and exporting problems (Ključnikov et al., 2022), higher costs (Çelik & Çevirgen, 2021; Bittucci et al., 2021; Msomi & Nzama, 2022), when implementing their market and financing decisions into the practice (Dvorský et al., 2020; Kocisova et al. 2018; Samanta, 2022). In this regard, investigation of suitable statistical demand forecasting model for both SMEs and large enterprises might create a value addition for the related academic literature. Although some other researchers state the importance of various business (Metzker et al., 2021b; Gavurova et al. 2022), and financial models for SMEs and larger enterprises in different topics (Stefko et al., 2020a; Tkacova et al. 2017), this study tries to find and emphasize the forecasting models for both SMEs and larger firms. This is another important fact that makes this paper differing from other studies.

In this study, we combine the historical data and the data from Google Trends (hereafter GT data), representing a new demand forecasting alternative (Kolková, & Ključnikov, 2021). Depending on some factors such as psychological factors (Stefko et al., 2022a; Gavurova et al. 2020a), people first search and gather information about a purchase (Stefko et al., 2020b) and then possibly make an actual one. In this regard, GT data may be more suitable for demand forecasting than historical data. The optimization of marketing processes is also very crucial for users and their satisfaction when making puchases (Stefko et al., 2022b; Gavurova et al. 2020b). But since this paper focuses on demand forecasting, the Facebook-developed model, called Prophet (Taylor & Letham, 2018), was chosen to represent the practice-based forecasting models. Our study works with the basic (*naive, ses, rfw, meanf*), more sophisticated statistical models (*Thetam, Tbats, ARIMA, and ETS models in automated model selection*), and models based on artificial neural networks developed in recent years.

These models are applied to four datasets that form the basis for determining the demand for bicycles. The first dataset contains information about the revenues, and the second one describes the number of orders, all in the case of bicycles sold in the selected e-shop in the Czech Republic. The third and fourth datasets describe the interest in the internet search for the keywords related to bicycles and cycling accessories provided by Google Trends in the Czech Republic. These data are compared with global demand, forecasted based on web searches. All datasets include both pre-pandemic and pandemic data. In addition, the data collection period included the period influenced by the covid pandemic to identify the forecasting technique's ability to deal with the intensive endogenic influence.

The structure of the paper is as follows. The literature review is presented in the first chapter, followed by a description of the methodological approach and data in the second, a presentation of the results in the third, and their discussion in the fourth. Finally, the last chapter concludes the results, presents research limitations, and describes the direction of future research.

1. Literature review

During the M4 Competition held in 2018, the scientific teams' representatives from research institutions and the business environment competed with their forecasting models. Surprisingly, three out of five winning models were developed in practice (see Table 1), and only two models represented the academic environment. Furthermore, the top ten included only one statistical model, combining quantitative and qualitative approaches. The other winning models were always a combination of approaches other than the statistical ones.

Table 1 The Results of M4 Competition

Model	**Author**	**Place of work of the author**	**Ranking**
Hybrid	Smyl, S.	Uber Technologies	**1**
Combination	Montero-Manso, P., Talagala, T., Hyndman, R. J., and Athanasopoulos, G.	University of A Corua, Monash University	**2**
Combination	Pawlikowski, M., Chorowska, A., and Yanchuk, O.	ProLogistica Soft	**3**
Combination	Jaganathan, S. and Prakash, P.	Individual	**4**
Combination	Fiorucci, J. A. and Louzada, F.	University of Brasilia a University of São Paulo	**5**
Combination	Petropoulos, F. and Svetunkov, I.	University of Bath and Lancaster University	**6**
Combination	Shaub, D.	Harvard Extension School	**7**
Statistical	Legaki, N. Z. and Koutsouri, K.	National Technical University of Athens	**8**
Combination	Doornik, J., Castle, J. and Hendry, D.	University of Oxford	**9**
Combination	Pedregal, D.J., Trapero, J. R., Villegas, M. A., and Madrigal, J. J.	University of Castilla-La Mancha	**10**

Source: *(Makridakis & Spiliotis, & Assimakopoulos, 2018)*

Therefore, it is necessary to consider why models created by the business environment are often more successful than the ones from academic teams when not all forecasting companies compete due to the know-how protection, and others use only already published models. The reason for that might be related to various factors that the business environment considers such as political and cultural issues, trade policy, tax system, protection of certain sectors and investors (Stefko et al., 2022c). Moreover, in many cases, an expert does not know which specific models they use. Table 2 lists some of the most important companies that deal with demand forecasting and offer products commercially.

While it is usually very complicated to verify the accuracy of some of the commercial predictive models due to the inability to access the exact codes, calculations, and know-how of these models, the forecasting competition gives the researchers a significant advantage forcing the authors to publish calculation codes.

The winning Uber model uses a computational graph system of a dynamic neural network, blending the standard exponential smoothing model with advanced short-term memory networks into a common framework. The result is a hybrid and hierarchical forecasting method. Two exciting features characterize the method: it uses statistical models of exponential smoothing (exactly Holt's and Holt-Winters' models with multiplicative seasonality) in combination with LSTM networks, and the second peculiarity is the use of a hierarchical structure. Furthermore, the author deseasonalized and adaptively normalized the selected data. As a result, the method generated accurate forecasts for most time series, especially monthly, annual, and quarterly ones. However, the accuracy was not the best for the cases of daily and weekly data. Nevertheless, the resulting accuracy surpassed all other authors. However, even after the end of the Competition, the author worked on improving the model (Bandara et al., 2020, Dudek et al., 2022).

Prologistica Soft presented a concept based on a combination of statistical methods with the statistical models weighted according to their performance. Here, they hand-picked the best-performing models for each type of series (Pawlikowski & Chorowska, 2020). The chosen methods included Naive, Naive2, Simple Exponential Smoothing, Exponential Smoothing (with automatic parameter choice), Damped Exponential Smoothing (automatic), ARIMA (automatic), modified Simple Theta, Optimized Theta, and econometric models (linear regression on different types of trends). All models were individually set.

Srihari Jaganathan presented his combined model (Jaganathan & Prakash, 2020) that was applied using Forecast Pro's commercial software package. Other combined models included the combinations of Naive/Snaive, Exponential smoothing (ETS), Dampened ETS, Bagged ETS, Exponential smoothing (ES)/complex exponential smoothing (CES), and general exponential smoothing (GES), Multi-aggregation prediction algorithm (MAPA), Temporal hierarchical forecasting (THIEF), Autoregressive integrated moving average (ARIMA), Theta, Hybrid Theta, Seasonal and trend decomposition using loess(STL) forecast, Trigonometric Box-Cox transform, ARMA errors, trend, and seasonal components (TBATS), Double seasonal Holt-Winters (DSHW), Multilayer perceptron (MLP)/extreme learning machines (ELM). Again, the models were chosen according to the subjective parameters, while primary factors in assessing the model selection included: the suitability of the methods for the given frequency, previous evidence of their performance in previous competitions and benchmarks, the availability of the software, their performance in the sample predictions in the M4 dataset.

The Prophet model created by experts from Facebook (Taylor & Letham, 2018) is another widely used one. The authors addressed the problems with creating high-quality forecasts, namely a large number of time series with different parameters. In particular, they draw attention to the fact that analysts with high professional knowledge of predictive analytics are still relatively rare. Therefore, their main challenge was to create a model that could be intuitively adjusted even by analysts with basic knowledge of time series. This model is widely applied for different purposes than initially intended. The applications included demand forecasting (Kolková & Navrátil, 2021), Taming energy, and electronic waste generation in bitcoin mining (Jana, Ghosh & Wallin, 2022), or oil production prediction (Ning, Kazemi & Tahmasebi, 2022). Wang, Du & Qi (2022), Ning et al. (2022) and Basakat et al. (2022) verified the feasibility of the Prophet model in practice.

Several other commercial products can be implemented in SAP and Streamline software, thus facilitating their operation for users. For example, IBM®Cognos Analytics is used to identify and model trends, seasonality, and time dependencies in data. Automated model selection and tuning make forecasting easy to use. These products thus enable the application even without knowledge of time-series modeling with automated data preparation. The entire data preparation and decomposition process are automatic if the system recognizes the entered data as a time series. It only uses exponential compensation models for forecasting.

Forecast Pro software offers a more extensive range of methods, including machine learning and dynamic regression. However, Forecast Pro offers three types of programs for purchase that may differ in their use of models. The most expensive program is currently priced at $9,995 for an annual license, maintenance, and support for the first year of the license. For example, the paid version of Forecast Pro was used in some time series (Jaganathan, & Prakash, 2020).

Of course, even Microsoft did not lag in creating forecasting tools and offered the Microsoft Azure Machine Learning product with the Stream Analytic tool. Microsoft (using Event Hubs) enables real-time data collection, then Stream Analytic aggregates and edits the data, using machine learning to select and run a prognostic model Microsoft Azure subsequently. Another Microsoft product, Power BI, is used for the final visualization of the results. Microsoft allows users to generate a statistical base forecast based on historical data, with the visualization of demand trends, confidence intervals, and forecast adjustment. In addition, Microsoft Azure can remove outliers and measure model accuracies.

Oracle and JD Edwards or Epicor belong to the other group of less-known products. Table 2 lists the most well-known methods currently used in commercial products.

Table 2 The most famous forecasting model providers and their models

Provider	Model	Method used	Reference
ProLogistica Soft	ProLogistica TREND	Naive method, weighted moving average, exponential smoothing, SARIMA, ARIMA X13	https://prologistica.pl/bazawiedzy/prognozowanie-popytu-i-planowanie-sprzedazy.html
IBM	IBM Cognos Analytics	ETS models	https://www.ibm.com/docs/cs/cognos-analytics/11.1.0?topic=d-forecasting
Forecast Pro	FP100	Machine learning model, exponential smoothing, Box-Jenkins method, Dynamic regression, event Models, Multiple-Level Models, Croston's intermittent demand model, moving averages, naive method.	https://www.forecastpro.com/solutions/forecast-pro/forecasting-methods/
	FP		
	FP TRAC		
Microsoft	Microsoft Azure (Stream analytics)	Machine learning model, unspecified statistical methods	https://docs.microsoft.com/cs-CZ/azure/architecture/solution-ideas/articles/demand-forecasting
	Microsoft Dynamics AX 2012	ARIMA, ARTxp	https://www.microsoft.com/en-us/download/confirmation.aspx?id=43128
Programs that can be implemented in SAP	GMDH Streamline	Unspecified statistical methods, machine learning model	https://gmdhsoftware.com/documentation-sl/statistical-forecasting
	SAP F&R	Unspecified statistical methods, regression analysis	https://help.sap.com/saphelp_scm700_ehp02/helpdata/en/8d/e2742de6dc455e900652ba8be6338c/frameset.htm

	Forecast in BW-Integrated Planning	Average, Floating Average, Weighted Floating Average, Linear Regression, Seasonal linear regression, Simple Exponential Smoothing (Constant Model), Simple exponential smoothing with alpha optimization (constant model), Linear exponential smoothing (trend model), Seasonal Exponential Smoothing (Season Model), Seasonal trend exponential smoothing (seasonal trend model), Croston model, Automatic Model Selection	https://help.sap.com/doc/saphelp_nw73ehp1/7.31.19/en-US/4c/af369d0cf30780e10000000a42189b/content.htm?no_cache=true
ORACLE and JD EDWARDS	Forecasting methods	Percent Over Last Year, Calculated Percent Over Last Year, Last Year to This Year, Moving Average, Linear Approximation, Least Squares Regression, Second Degree Approximation, Flexible Method, Weighted Moving Average, Linear Smoothing, Exponential Smoothing, Exponential Smoothing with Trend and Seasonality.	https://docs.oracle.com/cd/E16582_01/doc.91/e15111/und_forecast_levels_methods.htm#EOAFM00165
EPICOR	Forecasting methods	Weighted Average	https://www.epicor.com/en-us/industry-productivity-solutions/manufacturing/

Source: *own compilation according to references*

The demanding practical applicability, in combination with the consideration of whether the potential gain in accuracy could justify the added complexity and computational requirements, is a significant concern in the case of more complex forecasting methods. The study by Gilliland (2020) deals with the issue of the added value of machine learning approaches in forecasting. Green & Armstrong (2015) also criticize complex forecasting methods. However, Gilliland is mainly concerned with what is the one-dimensional improvement in accuracy worth. An apparent consideration here is that accuracy improves as the computation time increases. Table 3 presents an evaluation of the selected methods concerning the running time.

Table 3 Running times of selected methods and accuracy

Author	**sMAPE**	**MASE**	**Runtime (min.)**
Smyl	11.374	1.536	8056
Montero-Manso et al.	11.72	1.551	46108.3
Legaki & Koutsouri	11.986	1.601	25
Theta	12.309	1.696	12.7
ARIMA	12.669	1.666	3030.9
Naïve2	13.564	1.912	2.9
Naïve1	14.208	2.044	0.2

Source: *(Gilliland, 2020)*

A sizeable computational time is not necessarily a reason for discarding methods and not using them. Smaller enterprises can perceive the higher related costs and the need to employ experts as a specific constraint in using more complex methods. This peculiarity is typical for current business activity, even considering the increasing demand for IT products implementation in business management (Balcerak & Woźniak, 2021; Luchko, Arzamasova &

Vovk, 2019; Roshchyk et al., 2022; Szeiner et al., 2022), including artificial intelligence-based ones (Bencsik, 2021; Šuleř & Machová, 2020) and other digital tools of modeling and data collection within management systems in enterprises (Adda et la., 2021; Akimova et al., 2020; Bilan et al., 2017; Mura & Hajduová, 2021; Virglerová et al., 2022; Jeza & Lekhanya, 2022). Therefore, we also perform a multicriteria evaluation of the models in this study. According to Gilliand (2020), a more accurate forecast alone does not necessarily bring better results to the company. A more accurate forecast must also be interpreted correctly, leading to better business decisions. In some cases, there is no pressure or need for businesses to improve their forecasting models, as several inexpensive and reasonably reliable methods are sufficient. The use of more complex ML models in practice is still limited to large enterprises.

Kolková et al. (2022), in their research, focused on SMEs, and large enterprises, confirmed that SMEs do not widely use quantitative methods for their decision-making. The main reason for not using quantitative methods in SMEs was that they are too academically demanding and that their use in practice is often unrealistic due to their complexity. Companies of all sizes mostly use quantitative methods only to evaluate firm performance. In contrast, a minimum of companies use business simulation or evaluation of dependencies. However, most companies still focus on forecasting, although not at the top of it. Forecasting future business development is considered the most for future research (Kolková et al., 2022). At the same time, the research should lead to simplification and more direct applicability and interpretability of methods.

2. Methodological approach

This research uses the procedure presented in Figure 1 for demand forecasting. The exploratory data analysis was performed after data collection. Subsequently, the chosen methods were divided into two groups: methods developed in academic practice and those developed in the business sphere. The applied methods developed in the academic sphere include the basic (*naive, ses, rfw, meanf*) and more sophisticated statistical and hybrid models (*Thetam, Tbats, ARIMA, and ETS models in automated model selection*) and models based on artificial neural networks abbreviated as nnetar. The Facebook-developed model, called Prophet (Taylor & Letham, 2018), was chosen to represent the practice-based forecasting models. However, its functionality has not yet been verified in the M Competition.

After applying these models, their accuracy was calculated according to selected indicators (RMSE, MAE, MASE). Subsequently, other evaluation criteria were assigned: knowledge of the researcher and computing power of the scales. Finally, Saaty's method was selected for multicriteria evaluation. Its suitability was proved by the studies of Borovcová and Špačková (2018), Peterková & Franek (2018) or Mikušová & Čopíková, (2016). It is obvious that, apart from the accuracy criterion, the other criteria will be strongly interconnected with the company's size. Therefore, the multicriteria evaluation was calculated separately for large companies and SMEs. Since securing a suitable worker and adequate computing power for time series processing is more challenging in the case of SMEs, the weights of these criteria for SMEs was increased.

According to the multicriteria evaluation results, the most accurate model will be selected, both from the group of models developed in academic practice and the corporate sphere. The entire procedure is summarized in Figure 1.

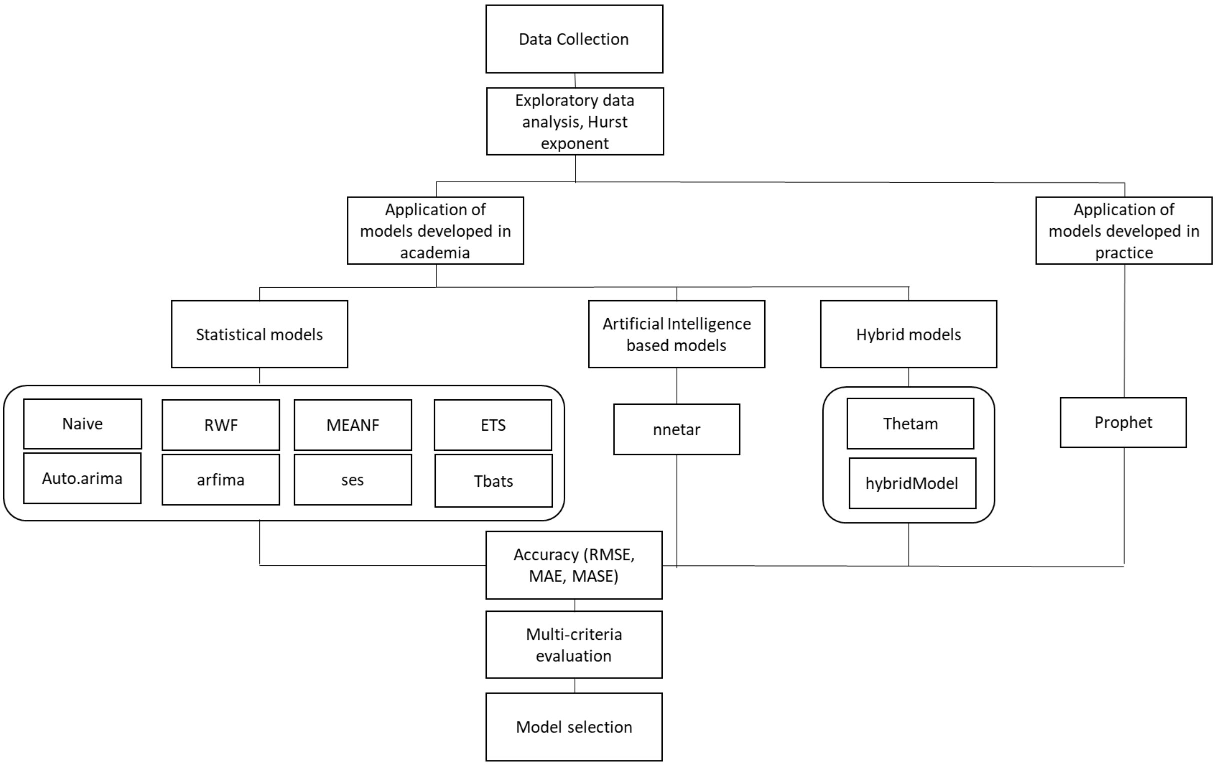


Figure 1 Methodical procedure for creating demand forecasting for bicycles
Source: *own compilation*

All calculations are performed in the R or Python language environment. The research team used the following R language packages: *Fpp3, forecast, fotecastHybrid, prophet, forecTheta*. In Python, the packages *Pandas, math, numpy, Prophet* were applied.

Data Description

This research utilizes the data describing the purchases of bicycles from the specialized online shop from the 1st of January 2019 to the 8th of October 2021, focusing on the time series of revenues and the number of product orders. These data were evaluated together with the time series of the GT data, focused on the terms related to bicycles for the period from the 1st of January 2019 to the 17th of April 2022. The daily-based data from the e-shops and weekly-based GT data were selected for the analysis. GT data values represent relative search interest to the highest point of the graph for a given region and time. A value of 100 represents the highest popularity of the term. A value of 50 means that the term had half the popularity. A zero score means that there was not enough data for the term.

GT data were selected for the Czech Republic and from around the world. The investigated e-shop is located in the Czech Republic. However, this market is relatively small and vulnerable in case of global changes. GT data have the same limitations related to the size of the country.

The data was the subject of a thorough descriptive extrapolation analysis. The selected results are shown in Table 4. The Hurst exponent is the fundamental parameter evaluating the randomness of the selected data (see Table 4). Since this exponent's value was higher than 0.5 for all monitored data, the data are not entirely random, and it is possible to trace patterns in them. Therefore, using advanced prediction models based on artificial intelligence is well justified.

Table 4 Extrapolative descriptive analysis

Time series	Min.	1st	Median	Mean	3rd	Max.	Hurst exponent
Revenues	0. 00	66 337	168 619	260 993	333 198	2 371 324	0.94
Number of orders	0.00	24.00	46.00	64.13	85.00	330.00	0.96
GT data (World)	55.00	69.00	77.00	76.36	83.00	100.00	0.89
GT data (Czech Republic)	1.00	21.00	28.00	28.44	38.00	53.00	0.86

Source: *own compilation*

Several outliers in the revenue and number of orders data were detected (see Figure 2). The data describing the purchases of bikes in the given e-shop increased by leaps and bounds due to the closure of brick-and-mortar stores during lockdowns, a direct cause of the Covid 19 pandemic. However, these fluctuations formed a relevant part of the demand and influenced the purchasing behavior of consumers; therefore, it was decided to keep these outliers in the time series. Due to the nature of the construction of GT data, these obviously cannot contain outliers.

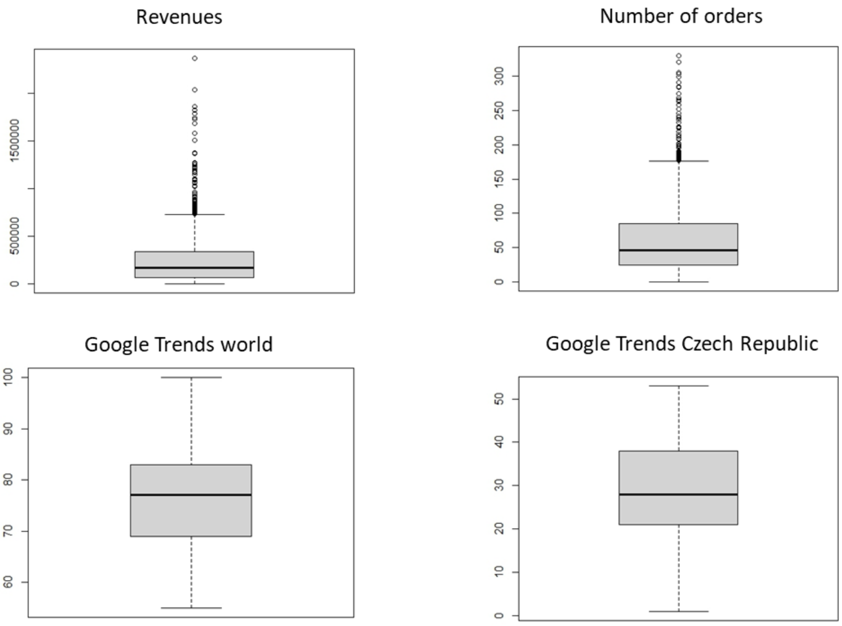


Figure 2 Box plot of time series
Source: *own compilation*

Forecast methods used

As mentioned above, the statistical and naive models were chosen based on the idea that data from the last period are used to forecast the next period without adjusting or forecasting the factors — the predictions made using the naive approach equal the final observed value. The Seasonal naive method is similar and applicable to highly seasonal data. In this case, we set each forecast to equal the last observed value from the same season (e.g. from the same month of the previous year). Rwf, another chosen statistical method, returns predictions and prediction intervals for a random walk with a drift model applied to *y*; the method is similar to the ARIMA(0,1,0) model with an optional drift coefficient. Finally, the meanf method represents the mean forecast and reflects the elementary idea of iid models applied to *y*. Here, we assume that the values are independently and identically randomly distributed (IID). The prediction of the first value is the sample average of the historical data.

ETS, auto.Arima and Tbats belong to the group of a bit more demanding ones. These models consist of several calculation methods from which the most suitable model is selected using a specific algorithm in the Forecast package. The most suitable model is the most accurate model. The Akaike information criterion (AIC) is used as a selection criterion. This criterion penalizes models with more parameters; another advantage is the possibility of choosing between additive and multiplicative errors in the models because AIC is not based on point predictions but on probabilities.

ETS methods have an automated ets function in the forecast package. According to Hyndman & Athanasopoulos (2018, 2021) *"each model consists of a measurement equation that describes the observed data, and some state equations that describe how the unobserved components or states (level, trend, seasonal) change over time."* The ets function is fully automated and selects the most accurate from 11 possible ETS models (Hyndman et al., 2002). The list of models is presented in Table 5.

Table 5 ETS forecasting methods

Shorthand	**Method**
ETS(N,N)	*Simple exponential smoothing*
ETS (A,N)	*Holt's linear method*
ETS (Add,N)	*Additive damped trend method*
ETS (A,A)	*Additive Holt-Winters' method*
ETS (A,M)	*Multiplicative Holt-Winters' method*
ETS (Add,M)	*Holt-Winters' damped method*
ETS (N,N)	*Simple exponential smoothing*
ETS (A,N,N)	*Simple exponential smoothing with additive errors*
ETS (M,N,N)	*Simple exponential smoothing with multiplicative errors*
ETS (A,A,N)	*Holt's linear method with additive errors*
ETS (M,A,N)	*Holt's linear method with multiplicative errors*

Source: *(Hyndman & Koehler & Snyder, & Grose, 2002)*

The *auto.Arima*, a fully automated function in the forecast package, uses a variation of the Hyndman-Khandakar algorithm (Hyndman & Khandakar, 2008). The model created in this way can be labeled as ARIMA(p,d,q), where p represents the degree of the autoregressive part, d is the degree of differentiation, and q is the degree of the moving average part. Akaike's Information Criterion (AIC) was chosen as the criterion for choosing the best-fit model:

$$AIC = -2log(L) + 2(p + q + k + 1), \text{ where}$$

L is the probability of the data, $k=1$, if the mean of changes between consecutive observations is not equal to 0; if it is equal to 0, $k=0$.

The second used criterion is the adjusted AIC_c, defined as

$$AIC_c = AIC + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2}$$

The last used criterion is the Bayesian Information Criterion (BIC), defined as

$$BIC = AIC + [log(T) - 2](p + q + k + 1)$$

The model is selected by minimizing AIC, AICc, or BIC, where AIC_c is a preferred utility.

The **ARFIMA** method is a particular case of ARIMA models, where the parameter *d* can take on even small values.

TBATS is an acronym created from the following abbreviations: Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, and Seasonal components. This model selects from various Box-Cox transformation models (with and without it, with and without trend, with and without trend damping, with and without autoregressive - moving average process). The TBATS model is described by the relation

$$\varphi p(L)\eta(L)y(\omega)t=\theta q(L)\delta(L)\varepsilon t, \text{ where}$$

L is the lag operator, $\eta(L)$ is $det(I-F\cdot L)$, $\delta(L)$ is $w\cdot adj(I-F\cdot L)\ g\cdot L+det(I-208F\cdot L)$, $\varphi p(L)$ and $\theta q(L)$ are polynomials of length p and q.

Nnetar is a model based on neural networks – simple mathematical models of the brain. They enable complex non-linear relationships between a variable and its predictors. The Nnetar model considers only feedforward neural networks with one hidden layer. Delayed time series values are used as inputs to the neural network, so the model contains neural network autoregression. The models are denoted by Nnetar(p,k), which expresses that there are p delayed inputs and k nodes in the hidden layer. Data is evaluated as seasonal, so adding the last observed values from the same season as inputs is valuable. Finally, the optimal number of delays is chosen again according to the AIC criterion.

The ***forecastHybrid*** model contains a combination of statistical models and models based on artificial neural networks (Shaub, 2020). Forecasts generated from auto.Arima, ets, thetaf, nnetar, stlm, tbats, and snaive can be combined with equal weights, weights based on in-sample error, or cross-validated weights. Cross-validation for time series data with user-supplied models and forecasting functions is also supported to evaluate model accuracy (Shaub, 2020)

The **Theta** model implements the function for forecasting univariate time series using several Theta models (Fiorucci et al., in 2016). The modified form presented by Shaub (2020) is used in this article. The method is based on the concept of modifying local fluctuations of time series using the Theta coefficient (denoted by the Greek letter θ). This coefficient is applied to the second difference of the time series, according to the relationship:

$$X''_{new} = \theta \cdot X''_{data}, \text{ where}$$
$$X''_{data} = X_t - 2 \cdot X_{t-1} + X_{t-2}$$

The initial time series is split into two or more Theta-lines, and each is then extrapolated separately. The predictions are then simply combined. A different combination of Theta-lines can be used for each forecast horizon.

The **prophet** model was developed by researchers at Facebook (Taylor & Letham, 2018) and was initially intended to be used only for daily data with weekly and annual seasonality and holiday effects. It was later extended to other types of data. The prophet is a non-linear regression model described by the relationship:

$$y_t = G(t) + s(t) + h(t) + \varepsilon_t, \text{ where}$$

$G(t)$ describes a linear trend, $s(t)$ different seasonal patterns, $h(t)$ are holiday effects, and ε_t is a white noise error term.

3. Results and discussion

The models were evaluated using the declared accuracy indicators, namely RMSE, MAE, and MASE. According to Hyndman & Athanasopoulos (2021), all data were divided into training and test data. A 30-day forecast was calculated on all data using selected models. The procedure was as follows: the model was created on the training data; the individual characteristics of the model were calculated; the model's accuracy was evaluated. At the next step, a prediction was made, and the model's accuracy was again calculated based on the test data (only the accuracy of the test data is relevant). However, it is also interesting to evaluate the accuracy of the training data. From the logic of the calculation, it is clear that the model should show high accuracy on the training data and lower accuracy on the test data. This difference becomes striking, especially for the models based on artificial intelligence (see Table 6).

The most accurate models based on artificial intelligence or hybrid models were used for revenue and GT data. The statistical models, especially the ARFIMA and the *meanf* model, appear to be the most accurate according to all evaluated criteria only in the case of the number of orders. Therefore, prediction on GT data works better on more complex and sophisticated models.

Table 6 Results of statistical models

Data		Number of Orders			Revenues			Google Trends in CZ			Google Trends in World		
Model		RMSE	MAE	MASE	RMSE	MAE	MASE	RMSE	MAE	MASE	RMSE	MAE	MASE
Statistical models													
	Training set	32.4105	23.5246	1.0000	184 952.2	133 917.3	1.0000	25.3126	17.1858	1.0000	21.2784	14.8407	1.0000
naive	Test set	106.9097	83.6339	3.5552	588 559.4	435 390.5	3.2512	19.7493	15.1930	0.8840	11.1552	8.5088	0.5733
	Training set	32.4105	23.5246	1.0000	184 952.2	133 917.3	1.0000	25.3126	17.1858	1.0000	21.2784	14.8407	1.0000
rwf	Test set	106.9097	83.6339	3.5552	588 559.4	435 390.5	3.2512	19.7493	15.1930	0.8840	11.1552	8.5088	0.5733
	Training set	34.1088	24.6229	1.0000	167 647.0	121 865.5	1.0000	18.1938	12.9646	1.0000	18.2672	13.3703	1.0000
meanf	Test set	92.0261	69.1025	2.8064	483 231.0	324 213.5	2.6604	12.7632	10.4726	0.8078	11.6229	10.1514	0.7593
	Training set	26.3583	18.9717	0.8065	143 837.7	104 701.2	0.7818	18.3155	13.0948	0.7620	17.5238	12.2949	0.8285
ETS	Test set	99.4589	75.7604	3.2205	507 753.8	345 488.8	2.5799	12.9947	9.7438	0.5670	10.7800	8.4803	0.5714
	Training set	26.1562	18.8576	0.8016	143 838.1	104 657.1	0.7815	18.1938	12.9646	0.7544	17.0820	11.9995	0.8086
auto.arima	Test set	99.5565	75.8559	3.2245	507 707.0	345 445.5	2.5795	12.7632	10.4726	0.6094	11.4880	9.9941	0.6734
	Training set	26.3126	19.0412	0.8094	143 960.9	105 543.3	0.7881	18.0148	13.0223	0.7577	17.1885	12.2954	0.8285
arfima	Test set	91.6369	68.5993	2.9161	484 499.0	323 998.0	2.4194	12.7879	10.3741	0.6036	11.4500	9.9339	0.6694
	Training set	26.3583	18.9713	0.8064	143 837.6	104 704.0	0.7819	18.3155	13.0946	0.7619	17.5238	12.2949	0.8285
ses	Test set	99.4621	75.7636	3.2206	507 743.9	345 479.6	2.5798	12.9957	9.7443	0.5670	10.7800	8.4803	0.5714
	Training set	26.2071	18.9062	0.7678	143 838.1	104 724.3	0.8593	18.3160	13.1069	1.0110	16.9255	11.8154	0.8837
Tbats	Test set	99.3288	75.6275	3.0714	507 744.8	345 480.5	2.8349	12.9862	9.7394	0.7512	11.8383	10.3277	0.7724
Artificial Intelligence Model													
	Training set	7.6734	5.2785	0.2244	83 069.4	61 338.4	0.4580	12.8774	9.9822	0.5808	13.0003	9.6391	0.6495
nnetar	Test set	108.4064	85.2127	3.6223	391 959.7	268 608.5	2.0058	17.5586	11.7111	0.6814	14.1124	12.4433	0.8385
Hybrid Models													
	Training set	26.3583	18.9713	0.8064	143 837.6	104 704.0	0.7819	18.3155	13.0946	0.7619	17.5238	12.2949	0.8285
Thetam	Test set	96.4754	72.6698	3.0891	500 574.4	337 658.7	2.5214	13.1501	10.0443	0.5844	10.7366	8.3802	0.5647
	Training set	22.3103	16.0777	0.6834	130 711.4	95 579.1	0.7137	16.9677	12.2509	0.7128	16.4373	11.5597	0.7789
hybridModel	Test set	100.2848	76.5596	3.2545	495 011.2	332 994.9	2.4866	12.6978	9.6795	0.5632	11.2645	9.7198	0.6549

Source: *own compilation*

The procedure in case of the Prophet model was as follows. The forecasting was started using the historical sales data using the parameters of the revenues and the number of orders. As a first step, the data were examined in big detail. Then, decompositions were performed using the Prophet package. Figure 3 confirms that it is possible to trace a similar trend for both time series, namely a sharp increase in the spring of 2021, followed by a decrease. This decrease was more partial in the case of revenues, while the number of orders decreased slightly. The sharp increase in spring 2021 corresponds to lockdowns in the first waves of the coronavirus pandemic. When stores were closed, e-shops were the only possible solution to satisfy the demand. However, the sharp increase in demand in this period was also due to a great desire for sports activities, and with the sports grounds closed, the bicycle appeared to be a suitable means to fulfill this desire. Moreover, the distance between accmmodations of individuals and touristic places can also determine the demand for the usage of bike (Stefko et al., 2022d).

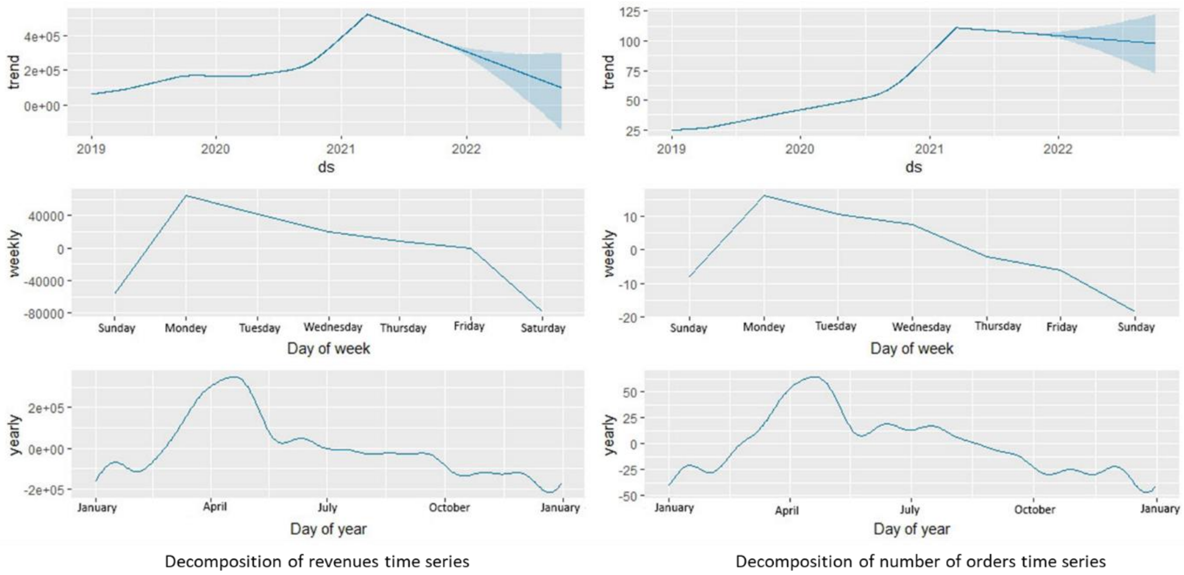


Figure 3. Revenue components and number of orders
Source: *own compilation*

Subsequently, a forecast was made. Since the data is affected by the significant influence of the fundamentals (lockdown and coronavirus pandemic), these atypical data will affect the forecast results. Figure 4 declares the actual values in black points (the prediction is expressed in blue color).

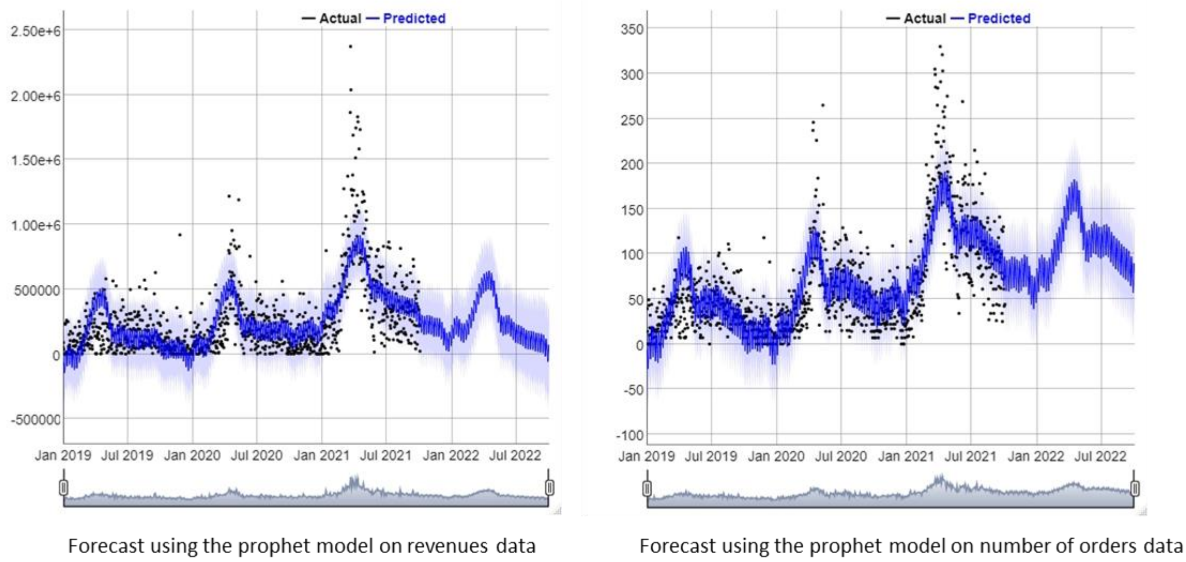
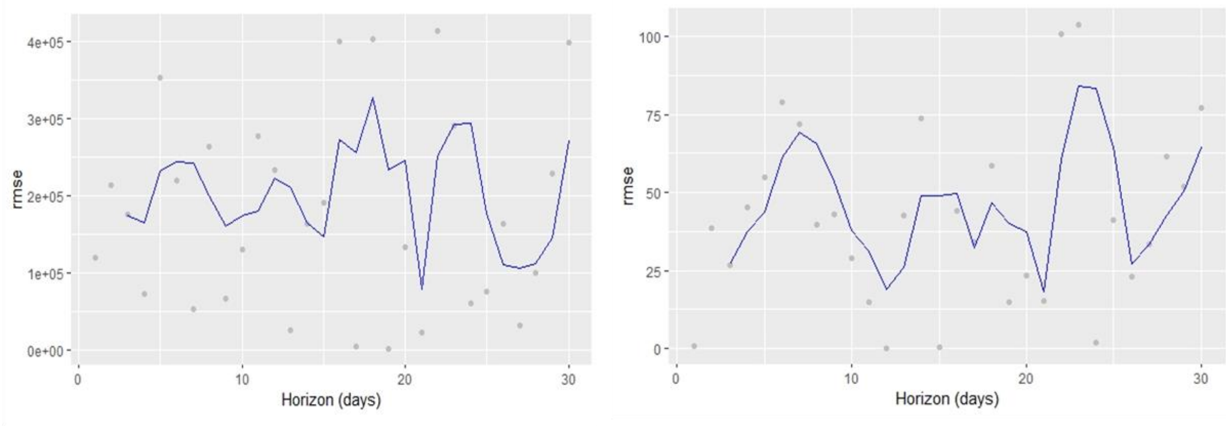


Figure 4. Forecast of revenues and number of orders
Source: *own compilation*

After analyzing the training data, the model predicted a correction of the fluctuations in the spring of 2021, although not entirely unequivocally. In particular, it assumed a lower revenue value increase than in reality. The model estimated the bicycle demand in 2019 more accurately using model training. Therefore, it is evident that essential fundamentals negatively affect the prediction result (as expected).

According to Figure 4, we can also see that the model does not expect the sharp increase in spring 2021 to be repeated (subsequently confirmed result). Therefore, the model was able to cope with one fundamental fluctuation.

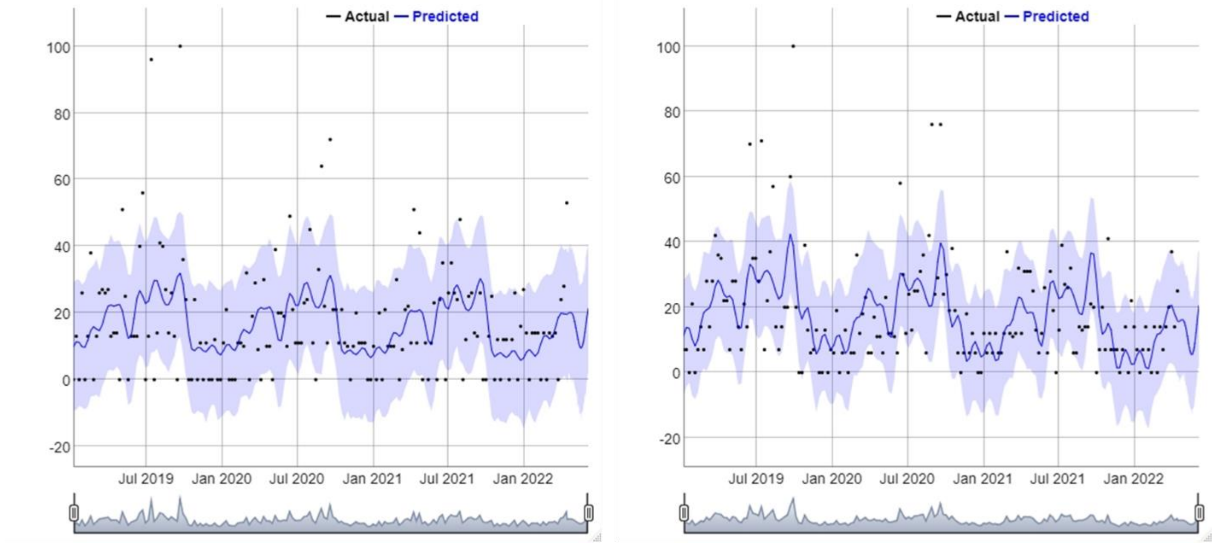
The Prophet model makes it possible to calculate the accuracy of individual days of the forecast by automated calculation. Figure 5 presents the forecast marked with a blue line; the dot is the RMSE depending on the days of the prediction. It can be seen that the degree of accuracy is most significant at the beginning, but it starts to fluctuate relatively quickly from day five onward. The forecast for data revenues shows a relatively large error in the RMSE, which does not increase much with further lengthening of the time horizon. For the number of orders, the model shows relatively good accuracy for the first 10-day forecast, after which there is already a relatively large error rate. However, this error rate is lower in subsequent comparison with other models.



RMSE for revenues for 30-days forecast RMSE for number of orders for 30-days forecast

Figure 5. RMSE of revenues and number of orders
Source: *own compilation*

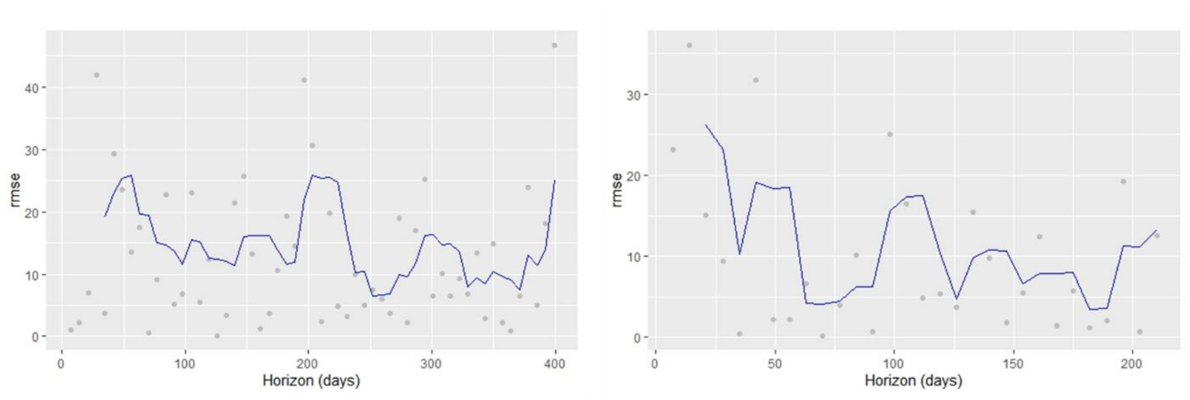
The same outputs were calibrated for GT data on a weekly basis with no justification for performing a weekly decomposition. However, it is interesting that the model shows several predictions of undefined values in the training data, even in 2019 (see Figure 6). On the contrary, in 2021 and part of 2022, the model predicted values quite accurately.



Forecast using the prophet model on Czech Republic GT data   Forecast using the prophet model on world GT data

Figure 6. Forecast Prophet of GT data
Source: *own compilation*

As for accuracy, it cannot be unequivocally stated for GT data that the accuracy decreases with the increasing time horizon of the prediction. Nevertheless, it is noticeable that the model error increases with sharp fluctuations and high volatility of the prediction.



RMSE - Czech republic GT data for 30-days forecast   RMSE - world GT data for 30-days forecast

Figure 7. Prophet RMSE of GT data
Source: *own compilation*

To enable comparison with Tab. 5, Tab. 7 shows only the accuracy for the 30-day horizon forecast, as was the case with the calculations of the other models. Here, monitoring the training data's accuracy is no longer necessary, as described in Figures 4 and 6. Table 7 presents the accuracy of the testing data. In historical data of the number of orders and revenues, prophet outperformed all previous models. For GT data, prophet outperformed all models for data from the Czech Republic. On the other hand, for global data, the Thetam model remains the most accurate, followed by the forecastHybrid model. Prophet was the third most accurate model.

Table 7 Accuracy of Prophet model

Data	Number of Orders		Revenues		GT in CZ		GT in the world	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
prophet	64.35533	63.51116	271096.55	241794.07	10.224375	8.080418	15.335897	12.146872

Source: *own compilation*

In the further step, the research team calculated the accuracy of the selected models. The accuracy results of the Prophet model, measured by RMSE, clearly showed that this model outperformed all previously used models despite its shortcomings in accuracy. The model had the best accuracy on both historical and GT data for the Czech Republic. Prophet ranked third using worldwide GT data. This result confirms that the origin of the model does affect the accuracy. The practice-originated model showed higher accuracy in all selected data types and outperformed academic-originated models based on artificial neural networks or hybrid models.

Our results confirm that the Prophet model works well on GT data, for which it was not originally built. Furthermore, this model is the most accurate among the selected models in the case of Czech GT data and was ranked third in accuracy in the case of the worldwide data, showing its good performance.

Our research results also confirm that the model's novelty is a criterion of accuracy. The models developed in the last five years were more accurate than the older models (see Table 8.) Therefore, it can be stated that the research in this area brings significant results and that the latest knowledge applied in forecasting leads to an increase in the accuracy of models.

Table 8 Evaluation criteria

Models	**Accuracy**	**Knowledge of the researcher**	**Computing power**
Statistical	1	4	4
Neural networks	2	2	3
Hybrid models	3	1	1
Model from practice	4	2	2

1 ..the worst, 4… the best

Source: *own compilation*

The atypical fluctuations that occurred as a result of the Covid pandemic were reflected in all models. However, in all models, they represented a short-term fluctuation in accuracy. In this case, mainly in the spring of 2021 due to the closure of brick-and-mortar stores. The accuracy of the Prophet model was again the highest, despite this foundation.

Accuracy in demand forecasting can be considered the most decisive criterion for choosing a model, and therefore according to the methodology in Figure 1, we would choose the Prophet model. However, other criteria can be substantial, namely, the demand for the researcher's knowledge or the demand for computing power. Therefore, Saaty's method was chosen for multicriteria decision-making. This method subjectively assigns preferences to individual criteria. The results of the evaluation are presented in Table 8. Preferences and weights were assigned based on the authors' professional assessment, and thus expressed their opinion on the issue under investigation.

Meanwhile, these criteria are mostly irrelevant in the case of large enterprises that employ data analysis and computing experts and have sufficient computing power. However, for SMEs, these criteria can be crucial. According to the research by Kolková et al. (2022), the complexity of models for small and medium-sized enterprises is often the main reason for not using them.

Individual criteria are assigned weights according to Saaty's method. Kolková et al. (2022) proved that large enterprises assign different weights to the criteria than SMEs. Therefore, this method was calculated separately for these two types of enterprises. While calculating the weights, it was estimated that large enterprises place more emphasis on the accuracy of the models at the expense of the demand for computing power and the researcher's knowledge. This is because researchers with relevant knowledge are usually available to large companies, and securing analysts' knowledge is not such a big problem. The same applies to computing power, which is no longer a problem for large enterprises. Therefore, they clearly prefer the accuracy of the model. The calculation of the weights for large enterprises is shown in Table 9.

Table 9 Calculation of the weights of Saaty's method for large enterprises

	Accuracy	**Knowledge of the researcher**	**Computing power**	**Geometric mean**		**the Scales**
accuracy	1.0000	9.0000	9.0000	4.3267	1.4422	0.8416
Knowledge of the researcher	0.1111	1.0000	1.0000	0.4807	0.1602	0.0935
Computing power	0.1111	0.3333	1.0000	0.3333	0.1111	0.0648
				Total	1.7136	1.0000

Source: *own compilation*

In contrast, SMEs often do not have such a large computing capacity or a separate predictive analytics department. For small businesses, prediction represents an additional cost to the statistician's remuneration and therefore places more weight on the researcher's knowledge. Computer technology is usually already available to SMEs today; however, some software products may still be unavailable due to their computer technology obsolescence. The calculation of the weights is shown in Table 10.

Table 10 Calculation of Saaty's method weights for SMEs

	Accuracy	**Knowledge of the researcher**	**Computing power**	**Geometric mean**		**the Scales**
accuracy	1.0000	1.0000	0.1667	0.5503	0.1834	0.1237
Knowledge of the researcher	9.0000	1.0000	1.0000	2.0801	0.6934	0.4677
Computing power	6.0000	1.0000	1.0000	1.8171	0.6057	0.4086
				Total	1.4825	1.0000

Source: *own compilation*

The resulting choice of method for large enterprises is shown in Table 11 and for SMEs in Table 12. The results differ concerning the size of the enterprises. Meanwhile, large enterprises should prefer the Prophet model and accuracy because accuracy is their most important criterion. For SMEs, on the other hand, statistical methods are still the most suitable, mainly because of their easy applicability, i.e., the low demands on computer technology and human capital.

Table 11 The resulting choice of method for large enterprises

Models	**Accuracy**	**Knowledge of the researcher**	**Computing power**	**Total**
Statistical	0.8416	0.3741	0.2594	1
Neural networks	1.6833	0.1870	0.1297	2
Hybrid models	2.5249	0.0935	0.0648	3
Model from practice	3.3666	0.2805	0.1945	4

1 ..the worst, 4… the best

Source: *own compilation*

Table 12 The resulting choice of method for SME

Models	**Accuracy**	**Knowledge of the researcher**	**Computing power**	**Total**
Statistical	0.1237	1.8708	1.6343	4
Neural networks	0.2475	0.9354	0.8171	2
Hybrid models	0.3712	0.4677	0.4086	1
Model from practice	0.4949	1.4031	1.2257	2

1 ..the worst, 4… the best

Source: *own compilation*

The results of this study confirm that the method's origin affects its accuracy and that methods developed by scientists in enterprises may have higher accuracy to methods developed in scientific workplaces of universities. Academic models were more precise only in the case of worldwide data. According to the evaluation based on Saaty's method, companies will also prefer it because of its lower demands on computing power and the researcher's possible knowledge.

The recently developed newer forecast models proved the increased accuracy. Except for the ARFIMA model, the new generation of statistical forecasting methods, the new methods are more accurate than the older ones.

The results confirm that the models can deal with non-standard data influenced by a strong foundation. Without the pandemic period, the forecast would probably be more accurate. However, even so, we can see from the test data that the forecast was fairly well estimated.

Conclusion

This study aims to identify the effectiveness of artificial intelligence-based and statistical forecasting models versus practice-based models for SMEs and large enterprise forecasting models developed in practice. The study compared the effectiveness of the practice-based Prophet model with the statistical forecasting models, models based on artificial intelligence, and hybrid models developed in the academic environment. Since most of the hybrid models, and the ones based on artificial intelligence, were developed within the last ten years, the study also answers the question of whether the new models have better accuracy than the older ones.

The exploratory data analysis was performed after data collection. Subsequently, the chosen methods were divided into two groups: methods developed in academic practice and those developed in the business sphere. The applied methods developed in the academic sphere include the basic (naive, ses, rfw, meanf) and more sophisticated statistical and hybrid models (Thetam, Tbats, ARIMA, and ETS models in automated model selection) and models based on artificial neural networks abbreviated as nnetar. The Facebook-developed model, called

Prophet, was chosen to represent the practice-based forecasting models. After applying these models, their accuracy was calculated according to selected indicators (RMSE, MAE, MASE). Subsequently, other evaluation criteria were assigned: knowledge of the researcher and computing power of the scales.

This research utilizes the data describing the purchases of bicycles from the specialized online shop, focusing on the time series of revenues and the number of product orders. These data were evaluated together with the time series of the GT data, focused on the terms related to bicycles. GT data were selected for the Czech Republic and from around the world. The data was the subject of a thorough descriptive extrapolation analysis. The data are not entirely random, and it is possible to trace patterns in them. Therefore, using advanced prediction models based on artificial intelligence is well justified.

The models were evaluated using a multicriteria approach with different weight settings in the case of SMEs and large enterprises. The results show that the Prophet model has higher accuracy than the other models on most time series. At the same time, the Prophet model is slightly less computationally demanding than hybrid models and models based on artificial neural networks. On the other hand, the results of the multicriteria evaluation show that statistical methods are more suitable for SMEs. The prophet forecasting method is very effective in the case of large enterprises with sufficient computing power and trained predictive analysts.

The main limitation of the research is related to the selection of data from the Czech Republic, where the market is relatively small and vulnerable in case of global changes. This limitation is valid, especially concerning the historical time-series data. The research's further direction may include applying this methodology to data from individual countries and their subsequent comparison. Another possible extension of the study is the inclusion of other models developed in practice and verifying their accuracy and other parameters.

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