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Demand forecasting: an alternative approach based on technical indicator Pbands

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Abstract

Research background: Demand forecasting helps companies to anticipate purchases and plan the delivery or production. In order to face this complex problem, many statistical methods, artificial intelligence-based methods, and hybrid methods are currently being developed. However, all these methods have similar problematic issues, including the complexity, long computing time, and the need for high computing performance of the IT infrastructure.
Purpose of the article: This study aims to verify and evaluate the possibility of using Google Trends data for poetry book demand forecasting and compare the results of the application of the statistical methods, neural networks, and a hybrid model versus the alternative possibility of using technical analysis methods to achieve immediate and accessible forecasting. Specifically, it aims to verify the possibility of immediate demand forecasting based on an alternative approach using Pbands technical indicator for poetry books in the European Quartet countries.
Methods: The study performs the demand forecasting based on the technical analysis of the Google Trends data search in case of the keyword poetry in the European Quartet countries by several statistical methods, including the commonly used ETS statistical methods, ARIMA meth-

od, ARFIMA method, BATS method based on the combination of the Cox-Box transformation model and ARMA, artificial neural networks, the Theta model, a hybrid model, and an alternative approach of forecasting using Pbands indicator. The study uses MAPE and RMSE approaches to measure the accuracy.
Findings & value added: Although most currently available demand prediction models are either slow or complex, the entrepreneurial practice requires fast, simple, and accurate ones. The study results show that the alternative Pbands approach is easily applicable and can predict short-term demand changes. Due to its simplicity, the Pbands method is suitable and convenient to monitor short-term data describing the demand. Demand prediction methods based on technical indicators represent a new approach for demand forecasting. The application of these technical indicators could be a further forecasting models research direction. The future of theoretical research in forecasting should be devoted mainly to simplifying and speeding up. Creating an automated model based on primary data parameters and easily interpretable results is a challenge for further research.

Introduction

Time-series forecasting is one of the fundamental research problems of contemporary economics and business administration. In addition, demand forecasting reflects the companies' need to anticipate their purchases and plan delivery or production. According to many practitioners and the scientific community, demand forecasting is an essential element of logistics systems (Bruzda, 2020) and provides essential information for planning (Syntetos *et al*., 2016). Moreover, a good demand forecast can also be a significant competitive advantage for a company (Kolková, 2020).

A wide range of statistical and artificial intelligence-based forecasting methods are currently being developed. AutoML systems have also come to the fore in the last two years, where we are already dealing with controlled artificial intelligence (Šimeček, 2019). The quality of the forecast depends both on the perfection of the applied methodology and data quality. From this point of view, the most frequently applied method is the prediction based on the historical time series of past purchases, adjusted concerning the trend, missing values, and outliers.

However, at present, the possibilities of forecasting models shift from the forecasts based on the previous purchase data to the models evaluating customers' willingness or desire to purchase.

In order to verify the new predictive models, the researchers need to use specific datasets with the specific characteristics of predictability. The demand for poetry books has been relatively stable over time, since it is not a subject of unpredictable political and social shocks. Therefore, it is suitable for the application of new models and the verification of new methodologies. From this point of view, the use of Google Trends data seems to be interesting. Google Trends is a commonly used way of including customer expectations in forecasts. Vosen and Smith (2011) applied this approach for the first time in their study comparing indicators based on market research and Google Trends in 2011. Their study uses Google keyword search history. This study aims to verify and evaluate the possibility of using Google Trends data for poetry book demand forecasting and compare the results of the application of the statistical methods, neural networks, and a hybrid model versus the alternative possibility of using technical analysis methods to achieve immediate and accessible forecasting. Specifically, it aims to verify the possibility of immediate demand forecasting based on an alternative approach using Pbands technical indicator for poetry books in the European Quartet countries (further referred to as V4 countries). The use of Pbands technical indicator for demand forecasting is not described in the current scientific literature. The study utilizes Google Trends data or searches of poetry books in the V4 countries. Based on the results, the demand for poetry books in different V4 countries will be determined. The paper has the following structure. The second chapter presents the results of the literature review. The third part describes the research methodology and data. The next part provides information about the study results, followed by the chapters with the discussion and conclusion.

Literature review

The scientific and business community has long been wondering which forecast method is the most accurate and which is the most suitable to use for demand forecasts. Forecasting methods are still evolving, and scientists worldwide strive to find the most accurate method with a potential universal use. As early as 1979, Makridakis and Hibon organized the first forecasting competition called M-Competition to find the most suitable forecast method (Makridakis & Hibon, 1979). Although the competition round in 1982 did not identify a transparently winning approach, others rounds followed in 1993, 2000, 2020, and 2021 (Makridakis *et al*., 1993). The results of this competition started to be more attractive after 2000, due to the development of computer technology.

Makridakis and Hibon (2000) published the results of the M-3 Competition. They confirmed that simple statistical methods do not overcome more complex ones because especially the Box-Jenkins method and ARIMA models were much more accurate than others. In this competition, 3003 time series from various fields such as business, demography, finance, and economics were applied, and 24 researchers were involved. The combined model called Theta was the winning method.

The last finished competition round, called M-4 Competition, was held by Makridakis in 2018 (Makridakis *et al*., 2018). One hundred thousand time series were analyzed at this round, while new requirements were placed on participants. The results of the M4 Competition showed that the combination of several prognostic methods brings the best results. 12 out of 17 most accurate methods in this competition were mainly the combinations of the statistical models. However, the biggest surprise and the absolute winner of the M-4 Competition was the hybrid approach. The hybrid model was authored by Smyl (2020), a data scientist from Uber Technologies.

Smyl applied a hybrid model based on artificial neural networks and a statistical method inspired by exponential compensation. He used formulas based on exponential compensation for deseasonalization, time-series normalization, and advanced neural networks for extrapolation. The second most accurate method in this competition was the method, which combined seven statistical methods and one machine learning method. The weights here were calculated using a machine learning algorithm. This method was presented by the Spanish University of A Coruña and the Australian Monash University (Montero-Manso *et al*., 2020).

The suitability of using different forecasting methods is also discussed by Hyndman and Fan (2010), Gabor and Dorgo (2017), or Cerqueira *et al.* (2019). The author's previous research also brings the results of comparing statistical methods and methods based on artificial intelligence (Kolková, 2018, Navrátil & Kolková, 2019).

Many researchers engaged in this area also evidence the development of this discipline. Current research shifts demand forecasting to the field of fuzzy logic. For example, Shao *et al*. (2021) created a demand forecasting method with intuitionistic fuzzy case-based reasoning. This method combines the advantages of intuitionistic fuzzy theory and case-based reasoning. This forecasting method provides decision support for relief material requirements and provides a basis for resource allocation.

The subject of forecasting has also been very variable in recent years. For instance, statistical and AI-based methods are used to forecast overall building performance (Roach *et al.,* 2021) and tea leaves' sales logistics (Lin & Lin, 2021). In addition, the effective prediction of container volume provides decision support for the planning and operation of the ports (Altin & Celik, 2020), spare parts for the aircraft fleet of an airline company (Babai, 2020). Prognostic models based on fuzzy indifference systems are applied to the products of nail polishes in the case of a multinational cosmetic company (Souza *et al.,* 2021) and on the number of tourist arrivals in Montenegro (Karadzic & Pejovic, 2020).

The data used for forecasting are also a subject of scientific research worldwide. It turns out that the use of historical time series may not be sufficient for demand forecasting. Google Trends data, including the data about the keyword search history, can be used instead of purchase history data. Several studies have compared Google Trend and historical data. The research by Pai *et al.* (2018) evaluated stock market prediction based on historical trading data and Internet search trends from Google Trends. Subsequently, they used hybrid data as a combination of both approaches. Numerical experiments then indicated that this approach was the most appropriate one. Vosen and Smith (2011) used Google Trends as early as 2011 to estimate private consumption. The results in almost all computational experiments performed better using data from Google Trend. The Google Trends data was used by Bokelmann and Lessmann (2019) for forecasting the tourism demand. This research shows that using Google Trends is useful primarily for short-term forecasts. Another research by Choi and Ahn (2020) examines seasonal effects with the use of the same approach.

De Livera *et al.* (2011) used the statistical methods ARIMA, ARFIMA, ETS, and BATS for demand prediction. Furthermore, models based on artificial neural networks, described by Kolková (2019) and the Theta model according to Assimakopoulos (2000), were also used for demand prediction.

It turns out that the results of these models may have a limited application in business activities. In particular, the high complexity of the complex models leads to their low usage in business practice. Zellner (2001) already pointed out that using more complex models does not always lead to better results. Businesses, especially in the small and medium enterprises (SMEs) segment, often do not have enough experts to apply the complex models in practice. Therefore, the models with the potential of practical application should be more understandable and easy to use. Therefore, the presented research focuses on an alternative approach — using technical indicators for demand prediction. Technical indicators are straightforward to apply, and their outcomes are easy to interpret.

Nikolopoulos (2021) considers the studies based on the use of operations research (hereafter OR) and OR methods to be "the science of better." However, many authors focus on a different and more applicable approach, including supply chain forecasting (Rostami *et al.*, 2019) or human judgment and behavioral operations (Kremer, 2016).

Despite the outstanding efforts of researchers, the easily applicable and clearly defined demand forecast methods are still not accurate enough. Moreover, these methods have not been evaluated concerning their training requirements and research experience. Although this relationship is not essential in academia, their simplicity and comprehensibility are crucial topics for applying methods in business practice. Small and medium-sized enterprises are ready to use innovative approaches for their development (Civelek *et al*., 2021; Ključnikov *et al*., 2021), but they need easily applicable methods. At the same time, Nikolopoulos (2003) pointed out the need to create sophisticatedly simple models for practice. While forecast methods are still evolving and creating new ones, it is impossible to describe them all due to the limited scope.

Research method

This study utilizes several statistical and hybrid methods. The commonly used ETS statistical methods, accompanied by well-known and standard ARIMA methods, were applied at the first stage of the research. Furthermore, the ARFIMA method, an extension of the ARIMA method, and the method based on the combination of the Cox-Box transformation model and ARMA, namely BATS, were used. Subsequently, we used a method based on artificial intelligence, namely artificial neural networks and the Theta model, the winner of the M Competition. Finally, we used a hybrid model as a combination of selected previous models.

Forecasting based on technical analysis, specifically the Pbands indicator, was used as an alternative approach to the standard models described above.

Statistical models, neural network and hybrid model

ETS is a deterministic method developed in the late 50s (Holt, 1957; Brown, 1959; Winters, 1960). This model is an exponential smoothing-based model including trend (T), seasonal (S), and error (E) components. Forecasts are weighted averages of past values, the weights of which are gradually declining.

ETS models can be written using formulas (1), (2), (3), and (4),

$$y_t = l_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t, \text{ where} \tag{1}$$

$$l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t \tag{2}$$

$$b_t = b_{t-1} + \beta\varepsilon_t \tag{3}$$

$$s_t = s_{t-m} + \gamma \varepsilon_t, \tag{4}$$

where:

l_t the estimated level of the time series,
t and b_t trend estimates,
t and s_t represent the seasonality,
α, β and γ the weight coefficients.

AutoRegressive Integrated Moving Average (hereafter ARIMA) has three parts: autoregressive (AR), integrated (I), and moving averages (MA). The model is marked as ARIMA(*p,d,q*). Suppose we need to describe the seasonal component in the model. In that case, we include new components and label it as ARIMA(*p,d,q*)(*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 part of the moving average. The special cases of the ARIMA model can also be deduced as follows. If we want to describe the white noise as an ARIMA model, then it would look like this: ARIMA (*0,0,0*). A random walk would be described as ARIMA (*0,1,0*), and the moving average as ARIMA (*0, 0, q*). The Box-Jenkins method is used to estimate ARIMA models. ARIMA model can be written with formulas (5) and (6),

$$\varphi(B) w_t = \theta(B) \varepsilon_t, \tag{5}$$

where:

$$w_t = \Delta^d y_t \tag{6}$$

AutoRegresive Fractional Integrated Moving Average (hereafter ARFIMA) is a specific version of the ARIMA when the parameter *d* can have a value less than one. These models generally respect the fact that even very distant random variables can be correlated in the stationary processes. Therefore, these models are often referred to as long-memory time series models. The ARFIMA (*p, d, q*) model can be written by the formula (7),

$$\varphi(B)(1-B)^d y_t = \theta(B) \varepsilon_t \tag{7}$$

The BATS model is named as an acronym from the names of the other models that make it up. The BATS model is based on the Cox-Box transformation model, ARMA model, trend, and **s**easonal components. Appropriate arguments (ϖ, ϕ, p, q, m_1, $m_2 \ldots m_T$) must accompany this designation for defining Cox-Box parameters and damping the parameters *p* and *q* for expressing parameters of ARMA models. The seasonal periodicity is expressed by the arguments $m_1, m_2 \ldots m_T$. BATS model represents a generalization of the traditional seasonal models, allowing for more seasonal seasons (De Livera *et al*., 2011).

The human brain processes inspired the creation of Artificial neural networks (hereafter NNAR). NNAR is a learning system where the model learns the regularities from the time series values and applies them to the output. Although, according to previous research, these methods are the most accurate in the case of the training data, they may not be so accurate in the case of the test data (Kolková, 2019).

The output of a neuron is calculated when the sum of the inputs to the neuron x_i multiplied by their specific weights w_i exceeds a certain value, called the distortion. The neuron can be described in this way (8),

$$y_j = f\left(\sum_{i=1}^{m} x_i \cdot w_{j,i} - b_j\right) \tag{8}$$

where:

x_i a specific value for *i*-th input,
$w_{j,i}$ the weights of this input,
b_j the bias, *m* is the total number of inputs,
f the transformation function,
y the value of the outputs, all according to the logic in Figure 1.

In this study, the results are interpreted as NNAR (p, k), where *p* is the number of inputs and *k* is the number of hidden nodes, according to Hyndman *et al.* (2021).

The Theta model was developed by Assimakopoulos (2000), and it is based on modifications of local time series curves. We implement this modification using the Theta coefficient; therefore the model is called Theta. The model can be described by the formulas (9) and (10),

$$y_{new}(\theta) = \theta \cdot X_{data}, \tag{9}$$

where:

$$X_{data} = X_t - 2X_{t-1} + X_{t-2} \tag{10}$$

The Theta coefficient and the degree of deflation have the opposite relationship. The greater the degree of deflation becomes, the smaller is the Theta coefficient. If the Theta coefficient equals 0, the time series is truncated by a linear regression line.

The hybrid model is based on the research by Shaub (2020). This model combines previously mentioned models, namely ARIMA, ETS, Theta, BATS, and NNAR. The resulting model is then given by the weighted average of these models and can be written by the formula (11),

$$y(i) = \sum_{m=1}^{n} w_m \cdot f_m(i) \tag{11}$$

where:
w_m the weight of each *m* of the *n* forecast model,
$f_m(i)$ the individual model forecast for time horizon i.

The same methods as in the case of the individual models, namely root mean square error (hereafter RMSE) and mean absolute percentage error (hereafter MAPE), are used to measure the accuracy of the hybrid model (Hyndman & Koehler, 2006). RMSE is defined by the formulas (12) and (13),

$$RMSE = \sqrt{MSE}, \tag{12}$$

where:

$$MSE = \frac{1}{N} \sum_{p=n+1}^{N} \left(X_p - \widehat{X_p}\right)^2 \tag{13}$$

and MAPE is defined by the formula (14),

$$MAPE = \frac{1}{N} \sum_{p=n+1}^{N} \frac{\left|X_p - \widehat{X_p}\right|^2}{X_p} \tag{14}$$

The seasonal naïve method was chosen as the benchmark. It forecasts the value equal to the last value from the same season. In practice, we can use only a method that exceeds this benchmark. If more than one method exceeds the benchmark, the one with the best accuracy will be used.

Based on the recommendation of Janurová *et al.* (2016), the statistical program R using Rkward was used for the prognosis. We applied several software packages of different authors, specifically the *forecast* packages by Hyndman and Khandakar (2008) and Hyndman *et al.* (2021), *ggplot2* by Pedersen (2020), and *forecastHybrid* by Shaub (2020).

Alternative approach: forecasting based on technical analysis

Alternative tools for short-term demand forecasting, namely technical analysis indicators, will be used in this study. Technical analysis focuses on evaluating graphs and predicting price movements, either by analyzing the shapes of graphs or based on technical indicators. We will try to use the technical indicator Pbands for the demand forecast. We want to verify the hypothesis that a simple method based on Pbands can predict short-term demand at the same level of accuracy as complex statistical methods or methods based on artificial intelligence.

This indicator is based on Bollinger Bands, created by John Bollinger in the 1980s. According to the literature, the Pbands technical indicator was not used for demand forecasting based on Google Trends. However, recent research on monitoring a multi-array photovoltaic system (Vergura, 2020) and the optimal coordination of a new protection system for solar photovoltaic generators (Rajput, 2020) have used Bollinger bands. Pbands and Bollinger bands are usually used in forecasting securities, forex, and other financial market instruments (Kolková, 2016).

Bollinger bands are based on the typical stock price of an HLC series. Therefore, these are not suitable for demand forecasting. On the other hand, Pbands technical indication is more suitable because it can be constructed in the case of the univariate price series.

This indicator is based on the calculation of three curves. The middle curve shows the moving average of prices, in our case, the moving average of the historical time series of the searches of a poetry book in the V4 countries. These moving averages can take on a variety of parameters and can be specific to a particular type of time series. Simple moving average (hereafter only SMA) is the most commonly used one. The other two constructed curves are created by the vertical shift of the SMA by a certain number of standard deviations. Thus, the upper and lower curves form a kind of corridor in which the price or value of a given instrument moves.

SMA model is from now on referred to as the center and is defined by the formula (15),

$$SMA_n = \frac{1}{n}\sum_{c=1}^{n} X(c) \tag{15}$$

The Pbands-based approach searches for a channel around the SMA calculated according to a formula. This channel has the *up* (hereafter *up*) *and down* (hereafter *dn*) values enumerated according to the formulas (16) and (17),

$$up = SMA_n + F \cdot \sigma_n \tag{16}$$

$$dn = SMA_n - F \cdot \sigma_n, \tag{17}$$

where:

F the standard deviation multiplication constant,

n represents the number of the last historical values used to calculate the moving average.

σ_n the standard deviation calculated based on the relationship (18),

$$\sigma_n = \sqrt{\frac{1}{n}\sum_{c=1}^{n}[X(c) - SMA_n]^2} \tag{18}$$

In this paper, Pbands are constructed using SMA based on the last 20 historical values. The standard deviation multiplication constant value is 2.

A possible future decline or increase in demand is derived from both the *up* and *dn* bands. When the *up* band touches or intersects the center, it is possible to predict a decrease in demand in the nearest future. On the contrary, when the *dn* band touches or intersects the center, we can predict an increase in demand shortly.

The statistical program R and the *TTR* package are used for the calculation (Ulrich, 2020).

Data description and decomposition

The selected methods are applied to four data sets, describing the demand for poetry books. When exploring an alternative approach for forecasting, it is essential to use data without missing values or outliers. Based on the literature review, it can be expected that the same forecast method may not always be the most accurate despite the similarity of the data. The data of interest in the poetry book among the population of the V4 countries were selected for forecasting because they represent a rare example of unaffected shock demand.

The numbers in the data sets represent the relative interest in the search relative to the highest point of the graph for a given area and time. A value of 100 represents the highest popularity of the term. A value of 50 means that the term was half popular. A score of 0 means that not enough data was collected for the expression.

These data were collected for the V4 countries. This grouping includes the Czech Republic, Slovakia, Poland, Hungary. These countries had historically similar developments, and the population in the V4 countries was confronted with similar artistic activities and trends. Therefore, the modern history of these nations also tends to the idea of a similar orientation of the population.

The Czech Republic is the economic leader of these countries, although Poland has made the biggest economic leap in recent years. The Czech Republic is by far the best in GDP per capita. In 2020, GDP (nominal) per capita in the Czech Republic was $ 22,627 compared to $ 18,669 in Slovakia, $ 15,373 in Hungary and 15,304$ in Poland. The unemployment rate is also the lowest in the Czech Republic (only 3.1% in 2020). Of course, economic maturity is not necessarily in line with the interest in the poetry book.

Before forecasting, it is necessary to decompose the data and their description. The decomposition of data in the Czech Republic is shown in Figure 2, and in Slovakia is shown in Figure 3. The decomposition of Polish data of interest in classical literature in Google search engine is shown in Figure 4 and the Hungarian data in Figure 5.

This decomposition confirms that the trend in the Czech Republic is different from other V4 countries. Although the financial crisis's impact after 2008 is evident in all countries, this impact was the smallest in the Czech Republic and was followed by a sharp increase in interest in the poetry book. This increase in interest has been steady in recent years. In Slovakia, the financial crisis was followed by a sharp increase, which declined over time; a similar development can be found in the Hungarian data. Meanwhile, Poland is following a trend of a steady decline in interest in poetry books, which is gradually changing only with the onset of a coronavirus pandemic. During the coronavirus pandemic, interest in poetry books also increased in Slovakia, while Hungary, on the other hand, faces a declining trend. As for the seasonal nature of the data, they follow a similar development in all countries, namely the decline in interest in the summer holiday months.

Results

After decomposition, forecasting was started. First, it was carried out by methods already available in scientific research, namely statistical methods, the AI-based method, and the hybrid method, all following the theoretical knowledge described in the Research methodology.

Statistical models, neural network and hybrid model

Based on statistical methods and artificial neural network methods, forecasting for the Czech Republic was calculated with the results declared in the set of graphs in Figure 6. We used the seasonal naïve method, the models ETS(A,N,N), ARIMA(0,0,0) with non-zero mean, ARFIMA(1,0.22,0), BATS(1,{2,1},-,-) and neural network NNAR(15,8).

The same approach was used for data from Slovakia. The again used the seasonal naïve method and other models with the following parameters: ETS(A,N,N), ARIMA(0,0,0) with non-zero mean, ARFIMA(2,0,0), BATS(1,{0,0},0.8,-) and neural network NNAR(15,8). The results are described by the set of graphs in Figure 7.

In the case of Poland, we applied the seasonal naïve method, ETS(M,Ad,N), ARIMA(0,0,0) with non-zero mean, ARFIMA(2,0.38,2), BATS(0,{3,0},0.9,-) and neural network NNAR(14,8). Graphs describing the results are presented in Figure 8.

Models with the following parameters were selected as the most accurate in the case of Hungary: ETS(M,A,N), ARIMA(0,0,0) with non-zero mean, ARFIMA(4,0.17,1), BATS(0,{2,2},-,-) and neural network NNAR(15,8). The results are again visualized graphically in Figure 9.

Furthermore, the *forecastHybrid* package was used in the R language, and the Theta model was enumerated for all V4 countries. The results are shown graphically in Figure 10.

Hybrid models were designed as a combination of ARIMA, ETS, Theta model, NNAR, and BATS models. All models were always represented in the hybrid model with a weight of 0.2. The results of the models for all V4 countries are shown graphically in Figure 11.

Of course, only the assessment of the suitability of methods according to the graphical expression is not the most suitable solution. It is necessary to proceed to the analysis of the accuracy and selection of the method according to this criterion. Table 1 shows the accuracy results for all V4 countries.

The NNAR method became the most suitable method for data from the training set. This finding is in line with the previous research (Kolková, 2020). However, this finding does not prove the suitability of these methods for application in business, but it develops academic knowledge. While the accuracy of the test set is essential, in our case the results are not clear enough. While artificial neural networks are the most suitable method in the case of the Czech data set, a hybrid model is the most accurate in the case of Slovakia and Poland. Surprisingly, the simplest seasonal naïve method, which served as a benchmark, was the most suitable in the case of Hungarian data. None of the other selected methods exceeded the benchmark. Depending on the results, we can state that different methods are suitable for different data. This finding is in line with the results of Makridakis *et al*. (2018).

Alternative approach: forecasting based on technical analysis

The evaluation of statistical methods and methods based on artificial intelligence does not provide a clear guide on which method to use. It is always necessary to respect specific data and verify the best method to use for each dataset. Forecasting is an individual matter, and each data set must be considered separately. The use of methods cannot be generalized to a group of data with the same subject of forecasting. For each time series, it is always necessary to test a suitable method according to the standard procedure used in this study. For this reason, it is possible to consider alternative forecasting methods, which are also based on individual data monitoring.

Another argument may be the forecast horizon. As can be seen from the graphs in Figures 12, 13, 14, and 15, with the length of the horizon the quality of the forecast decreases, and an accurate forecast can be obtained practically only a few moments after the end of the historical time series. The business practice may also indicate that a forecast is not required for several months in advance in some industries, but an immediate forecast is sufficient to ensure supply logistics. For these reasons, it is certainly interesting to try the methods of technical analysis for forecasts. Pbands are only able to forecast instant predictions. In supply management, however, this is often the main requirement for forecasting models.

In this study, Pbands indicators based on a 20-day moving average were used as the center of the line. The down and up bands were created with the standard deviation multiplication constant with the value of 2.

Based on the results for the Czech Republic in Figure 12, we see a breach of the lower limit of the Pband, and we can, therefore, expect an increase in values in the coming months. This finding is in line with the most accurate method for the Czech Republic. The main limitation of Pbans application is that this method is suitable for an immediate forecast only.

For Slovakia, based on Pbands, it can be expected that its direction to the lower limit of Pbands will continue, see Figure 13. The hybrid models, previously selected as the most suitable for Slovakia, also predict a decline in demand, and this result is the same as in the case of Pbands.

For Poland (Figure 14), the method based on Pbands showed a breakthrough of the downline of the Pbands, which tends to predict growth.

However, the result of the hybrid models, previously selected as the most suitable for the Poland data set, is the same.

The Hungarian data shows the most interesting deep breakdown of the boundary of the Pbands, which leads to the assumption that there should be a turnaround and an increase in interest in poetry books in Hungary (see Figure 15). Unfortunately, none of the methods exceeded the benchmark for Hungarian data; therefore, none of the AI-based methods or the hybrid model are suitable for these values. On the other hand, the seasonal naïve method, a suitable representative of the statistical methods, predicts demand stagnation. However, caution is required when interpreting such different data. Moreover, the result cannot be considered unambiguous.

Discussion

The article presented the possibilities of demand prediction based on statistical methods, methods based on artificial intelligence, and hybrid methods. The methods were applied to 4 groups of data with the same subject of demand, namely the demand for books of poetry. The data set groups differed only in the countries of origin of the input data came. In addition, the countries were similar from the point of view of their historical and economic development. Nevertheless, the results do not reveal a winning method, universally valid for all countries. This finding is in line with the literature review, which showed the inexistence of a method with universal validity for all types of data. Although many researchers have sought to identify the universal method (Makridakis & Hybon, 2000; Makridakis *et al.*, 2018; Smyl, 2021; Montero-Manso *et al.*, 2020), they all were unsuccessful.

However, methods based on technical analysis have a fundamental advantage in processing speed. The classic forecast requires selecting methods, determining benchmarks, and performing calculations, which is time-consuming and computationally demanding. Furthermore, verification of the accuracy of the models is needed. The performance of all described steps allows proceeding to the determination of a suitable model for prognosis. All these steps are eliminated in the case of the methods based on technical analysis. The method is straightforward and may be sufficient for specific fields for getting immediate information about the situation in demand. Previous research (Kolková, 2020) shows that runtime, computing demand, and the researcher's experience can significantly change the possibilities of applying methods in practice. However, the required knowledge of the economist applying the models is low in the case of the alternative approach. The method used in this study is based on a very simple calculation procedure and is easy to interpret the results.

Another advantage is the band's determination in which the demand usually moves, which may also be helpful for logistics planning. Monitoring of the band using Google Trend data may be potentially helpful for other applications, like trends of customer loyalty monitoring (Khan *et al*, 2021) or changing trends in customers' shopping habits (Machová *et al*., 2021). Determining the band in which demand will move can thus respond to the impossibility of determining a universal forecast method.

This alternative approach has not yet been used for demand forecasting. The article opens a discussion for further scientific research of this approach.

Conclusions

Demand forecasting helps companies to anticipate purchases and plan the delivery or production. In order to face this complex problem, many statistical methods, artificial intelligence-based methods, and hybrid methods are currently being developed. However, all these methods have similar problematic issues, including the complexity, long computing time, and the need for high computing performance of the IT infrastructure.

This study aimed to verify the possibility of immediate demand forecasting based on an alternative approach using Pbands technical indicator for poetry books in the European Quartet countries in comparison with more traditional methods. The study results show that the alternative Pbands approach is easily applicable and can predict short-term demand changes. Furthermore, the Pbands method is suitable and convenient for monitoring short-term data describing the demand due to its simplicity. The methods based on technical analysis, namely Pbands, are a possible alternative in forecasts to complex statistical methods and methods based on the AI and hybrid method. According to the Pbands indicator, all data of the V4 countries without Hungary predicted the same results as more complex, time-consuming, and computationally demanding methods.

Of course, the use of technical analysis as a tool for demand forecasting has its shortcomings. First of all, it should be noted that this method is not suitable to forecast the long-term trend of demand. Pbands are used only for short-term estimation of demand development. This is due to the essence of technical analysis, which has always been used for short-term forecasting.

In further research, it is appropriate to focus on the parameters of Pbands. For the company's demand forecasting and logistics processes, it will also be interesting to work with the basic idea of Bollinger bands and the finding that 95% of the data is in a given band. The logistics of the supply process could therefore work with this idea.

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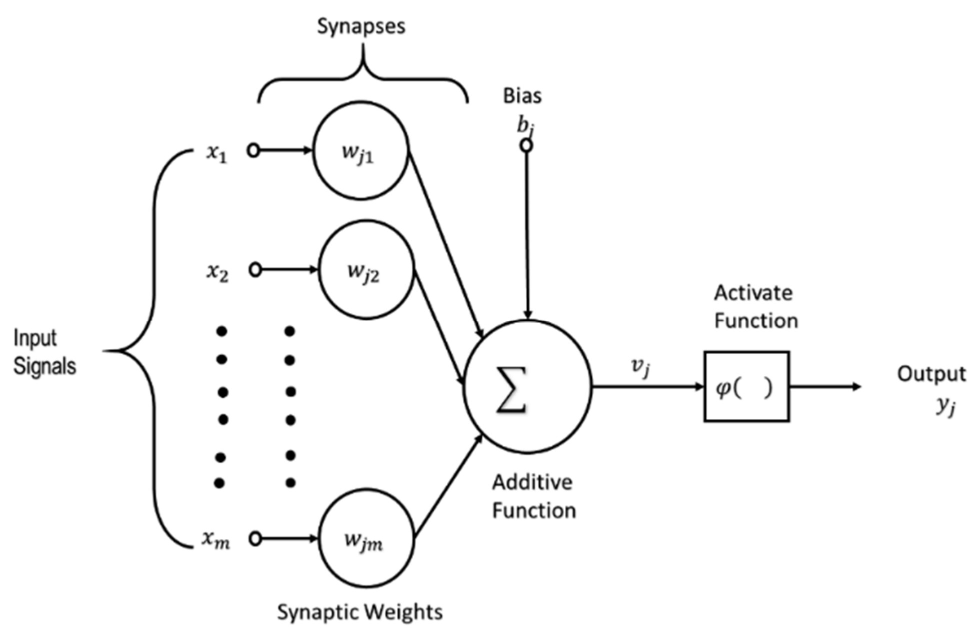
Annex

Table 1. Accuracy according to MAPE and RMSE

			Czech	Slovakia	Poland	Magyar
SNAIVE	**MAPE**	**Training set**	15.5740	21.5692	25.0317	16.4658
		Test set	23.9968	29.0216	33.9334	16.2331
	RMSE	**Training set**	9.8253	13.3188	15.3588	9.8839
		Test set	19.4205	14.0859	10.5471	6.7185
ETS	**MAPE**	**Training set**	15.5162	21.4263	38.9904	17.6089
		Test set	23.7234	29.0202	28.6037	21.4139
	RMSE	**Training set**	9.7869	13.2743	16.5551	10.1441
		Test set	19.0504	14.0848	7.3940	8.5424
ARIMA	**MAPE**	**Training set**	25.9225	31.6419	60.3276	20.5934
		Test set	25.6864	44.7896	80.1776	29.5138
	RMSE	**Training set**	14.3085	17.0132	23.7511	11.3406
		Test set	21.4431	17.4111	17.8558	11.0117
ARFIMA	**MAPE**	**Training set**	14.8564	20.1975	25.9060	14.4457
		Test set	24.7054	42.4503	42.1352	27.5927
	RMSE	**Training set**	9.1742	11.9514	12.9021	8.5435
		Test set	20.4084	16.6116	10.0793	10.3444
BATS	**MAPE**	**Training set**	13.8604	20.1063	24.6414	14.4378
		Test set	21.3799	31.4763	26.2088	21.4159
	RMSE	**Training set**	8.8007	12.4234	14.1663	9.0610
		Test set	16.9138	13.0549	6.9783	8.2487
NNAR	**MAPE**	**Training set**	0.3830	0.5958	1.6986	0.6303
		Test set	17.2283	23.4616	19.9100	18.7926
	RMSE	**Training set**	0.3146	0.4580	1.0180	0.4256
		Test set	15.4954	13.4317	7.6820	7.5782
Theta	**MAPE**	**Training set**	15.6581	19.7707	23.8775	15.8411
		Test set	33.2399	25.9485	45.4977	41.8301
	RMSE	**Training set**	10.9391	11.8613	-0.1057	8.8474
		Test set	29.2688	10.5372	12.6213	17.4189
Hybrid model	**MAPE**	**Training set**	10.6181	14.1555	19.1417	10.7936
		Test set	24.6539	24.1982	28.1582	23.8680
	RMSE	**Training set**	7.8507	8.6635	8.2199	6.1706
		Test set	21.5864	9.8133	7.3516	10.5362
The best	**MAPE**	**Training set**	nnar	nnar	nnar	nnar
		Test set	nnar	nnar	nnar	snaive
	RMSE	**Training set**	nnar	nnar	nnar	nnar
		Test set	nnar	hybrid	hybrid	snaive

Figure 1. Forecasting vy neural networks



Source: Haykin (1994).

Figure 2. Decomposition of Czech Republic data

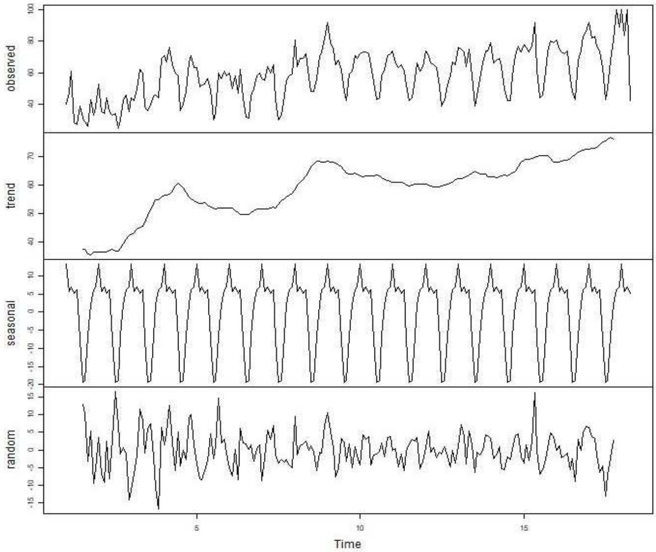


Figure 3. Decomposition of Slovakia data

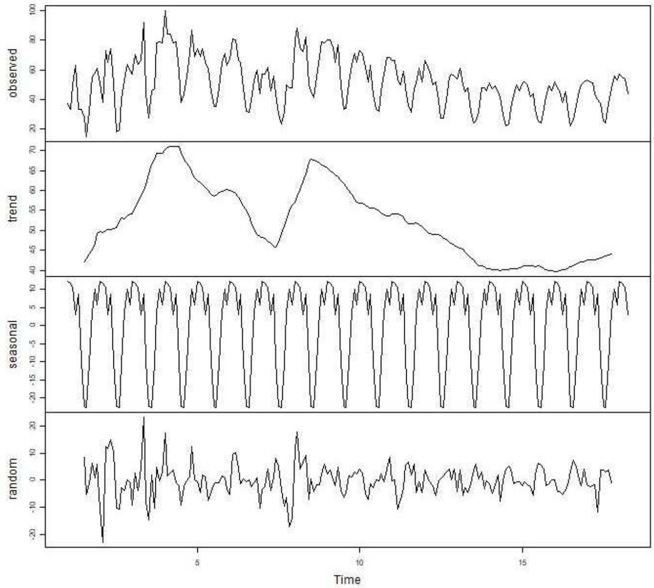


Figure 4. Decomposition of Poland data

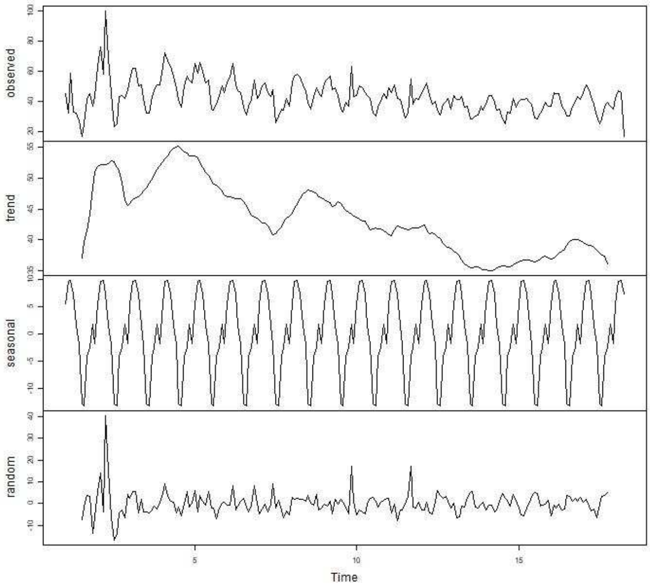


Figure 5. Decomposition of Magyar data

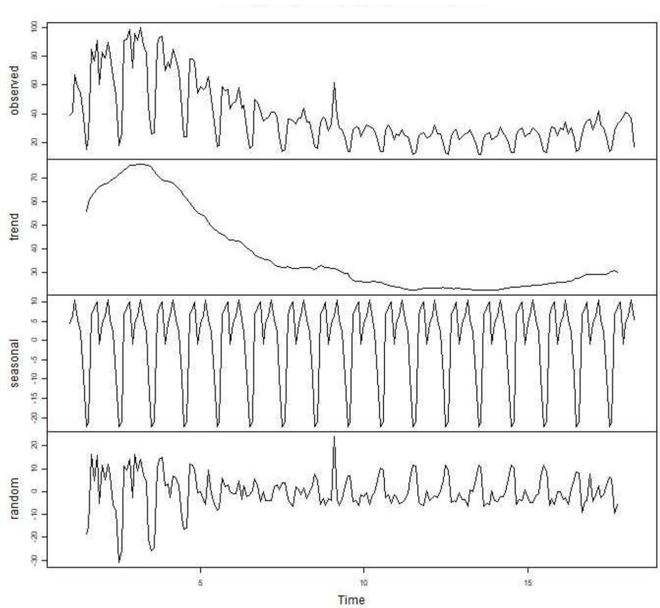


Figure 6. Forecasting by statistical methods and neural networks in Czech Republic

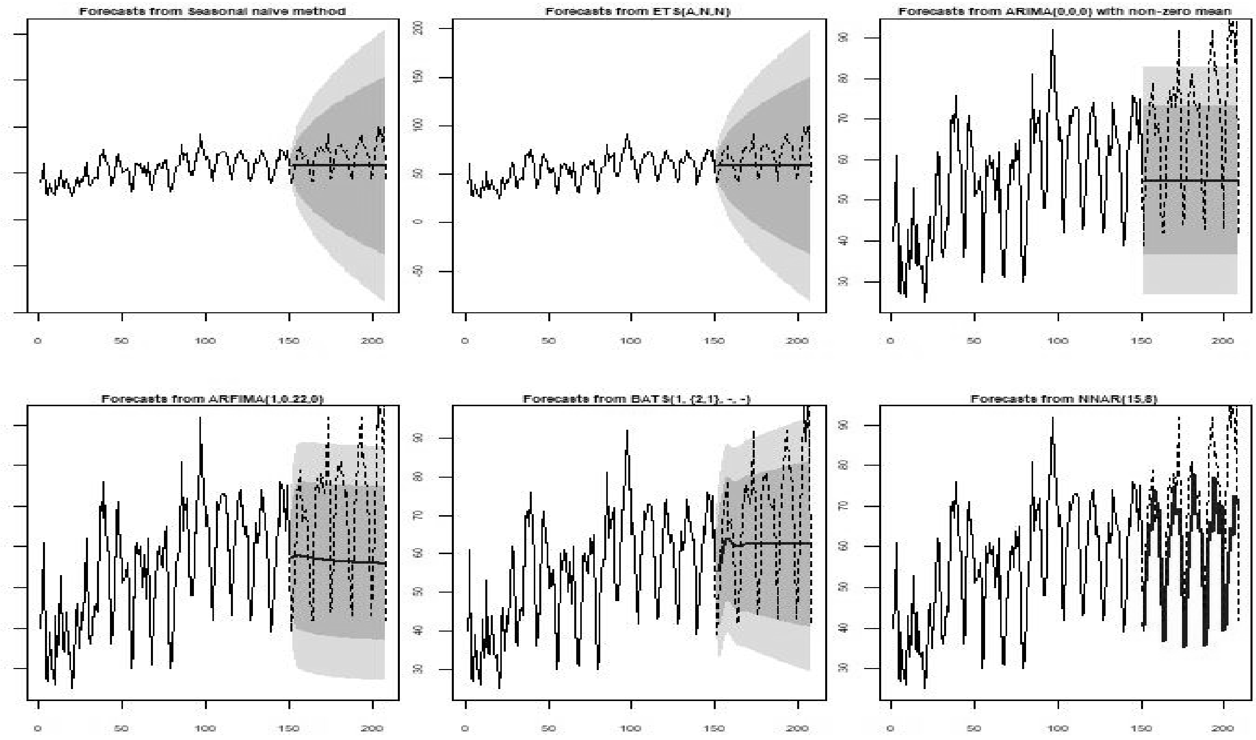


Figure 7. Forecasting by statistical methods and neural networks in Slovakia

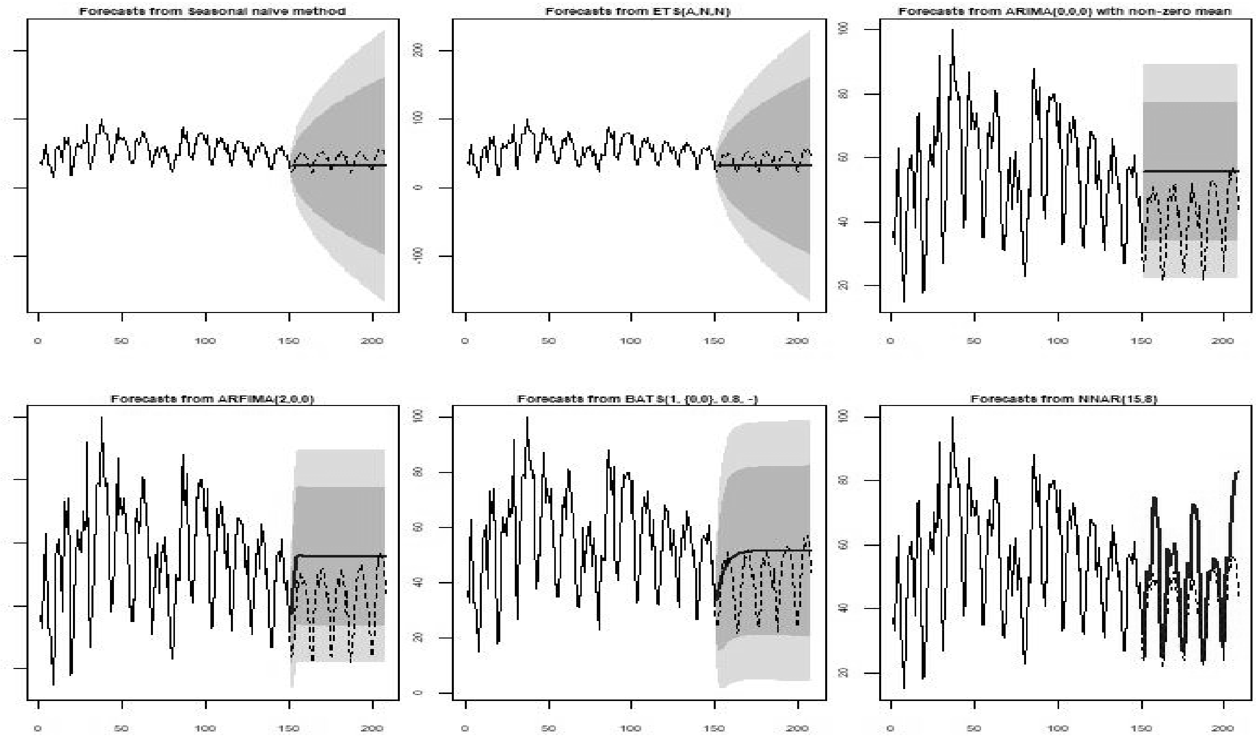


Figure 8. Forecasting by statistical methods and neural networks in Poland

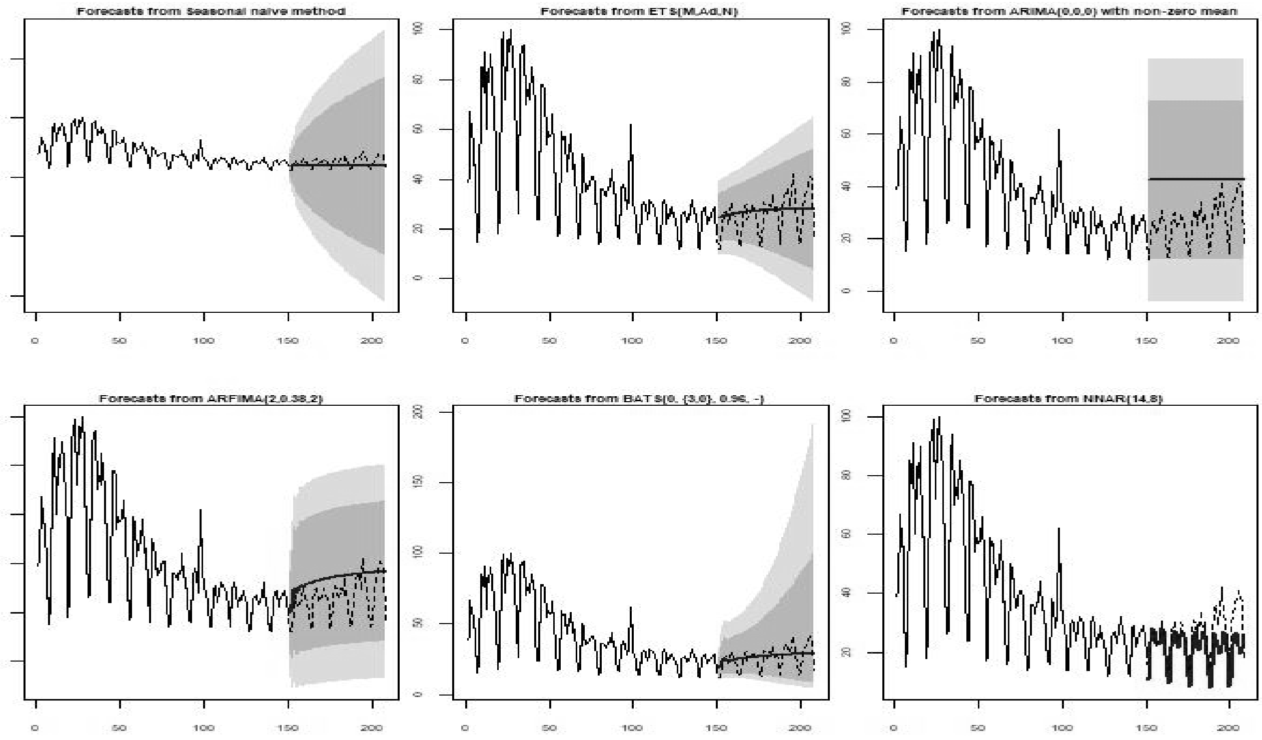


Figure 9. Forecasting by statistical methods and neural networks in Hungary

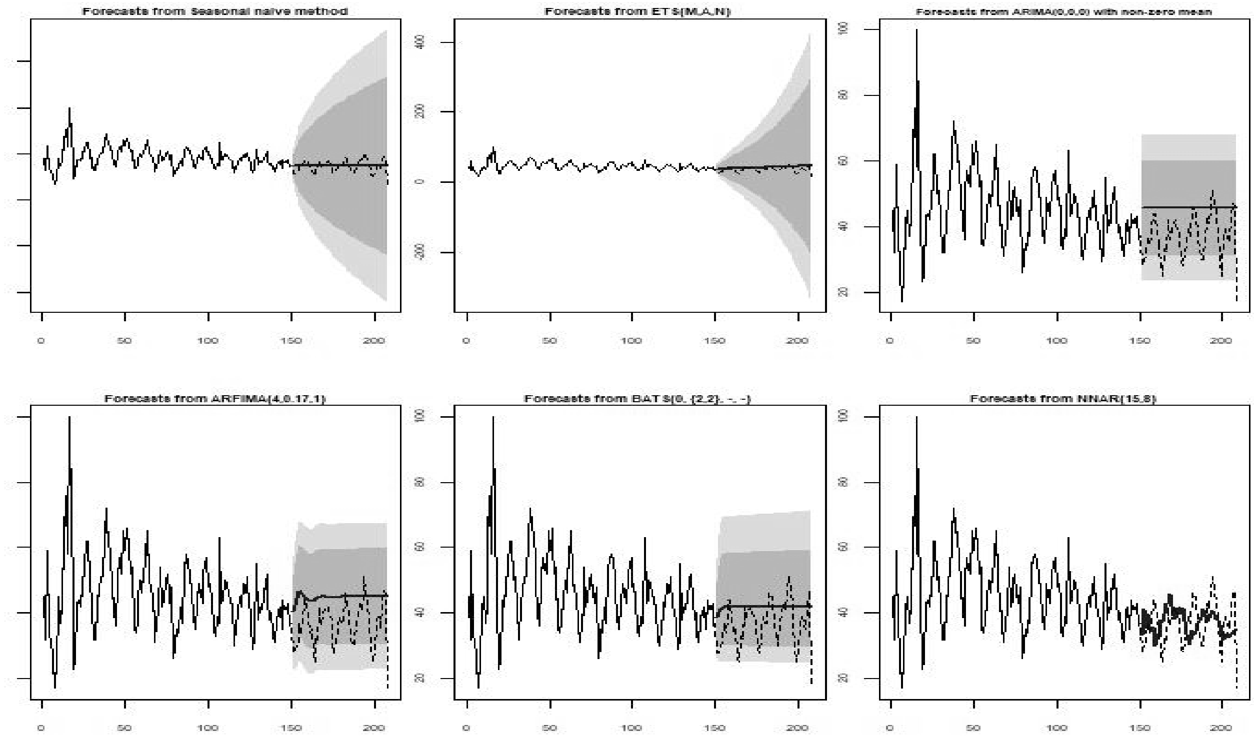


Figure 10. Model Theta in country V4

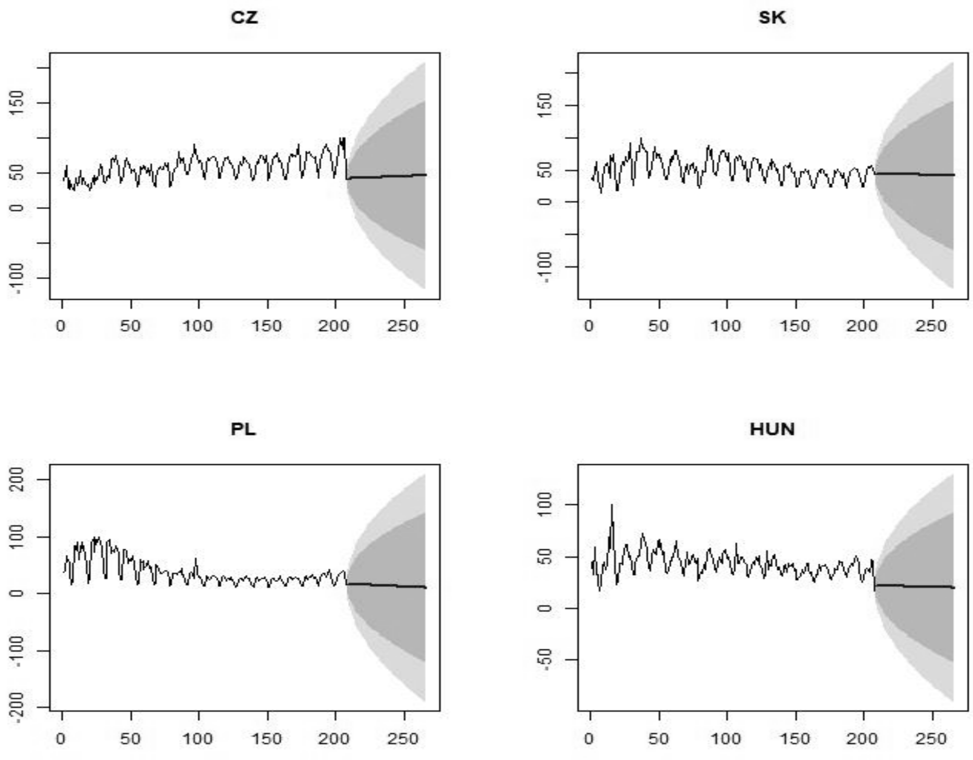


Figure 11. Hybrid model in country V4

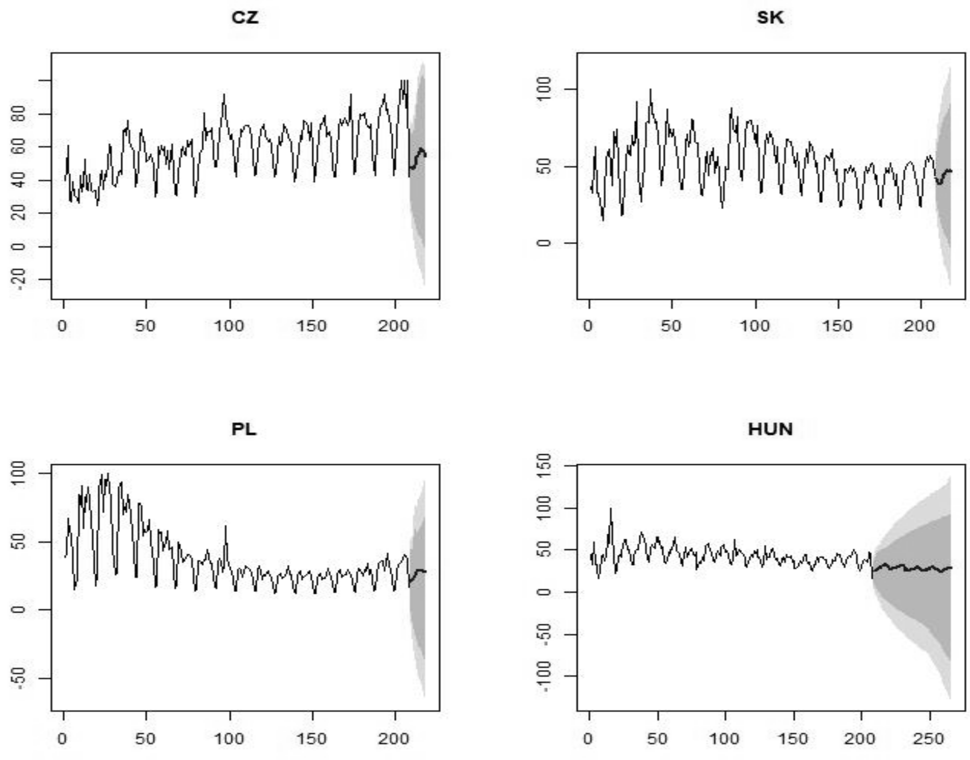


Figure 12. Pbands for Czech Republic data

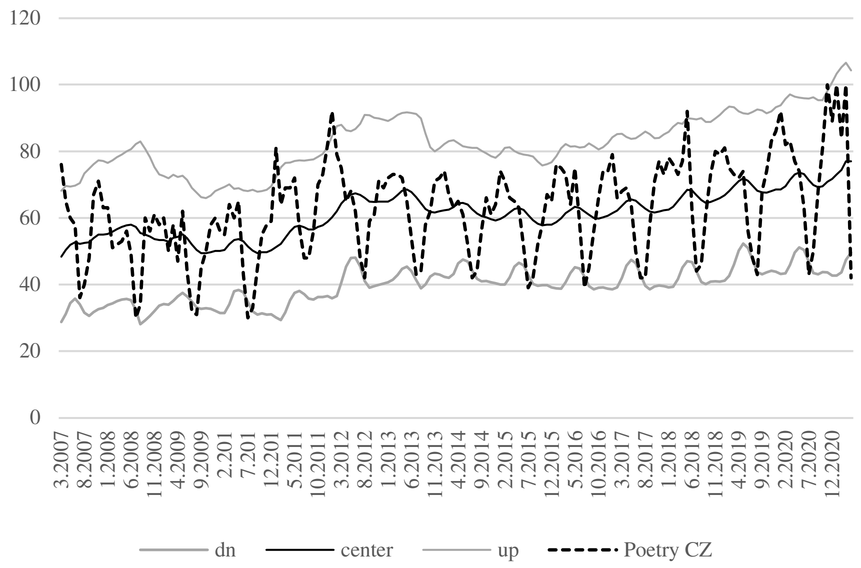


Figure 13. Pbands for Slovakia data

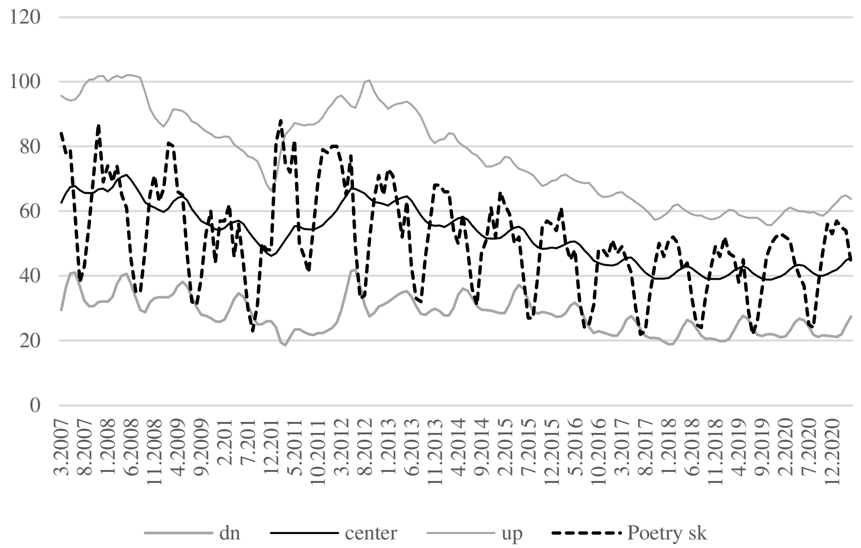


Figure 14. Pbands for Poland data

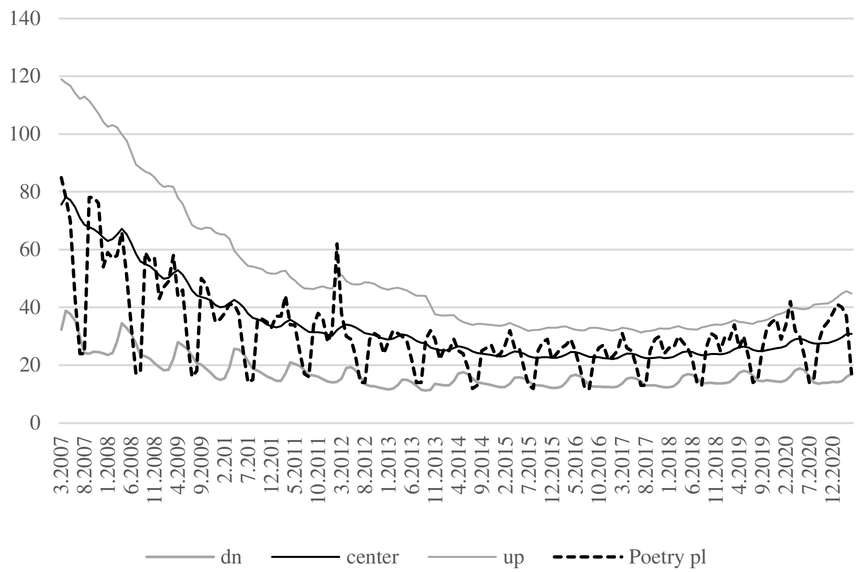


Figure 15. Pbands for Hungary data