Application of Exponential Smoothing Models and Arima Models in Time Series Analysis from Telco Area

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Abstract

The use of ICT has been steadily increasing in both business and social life. Apparently, the most essential communication technology today is a mobile phone. However, the use of mobile phones also has its downside, which is their impact on the environment, which is not negligible.

Despite the negative impact on the environment, few of us can imagine a life without a mobile phone. The mobile telecommunications market is one of the most important sectors of the modern economy. Analysing past developments - as well as predicting future developments - of indicators in this area plays a very important role in decision making, as in any other area of the national economy. The extrapolation methods have been the most often applied methods in the area of time series analysis and forecasting in practice. Currently, the combined methods in time series forecasting is more and more favoured. The main aim of this paper is an examination of applicability of the Box-Jenkins methodology models and the exponential smoothing models for providing extrapolation forecasts, but for past development modelling of selected indicators from the telecom area, too. Information on the indicators under study was collected on monthly and daily basis. Quality of the models selected was then assessed using the MAPE and AIC metric. In conclusion, a comparative analysis was performed of both the groups of models. The best individual models were further aggregated and quality of these was assessed using the same assessment criteria. SAS statistical system was applied for effective implementation of the analysis. The research has demonstrated that the exponential smoothing models can only be recommended for the analysis of indicators under study from the mobile telecom area. The detailed analysis has proved, anyway, a higher level of success with the combined models.

Keywords

ICT and environment, ICT and sustainable rural development, mobile telco services; time series; exponential smoothing models; Box-Jenkins methodology; combined models

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Introduction

The telecom market represents a sector developing very dynamically in not only the Czech Republic but also whole the world over. Several years have passed since the iPhone was first introduced to the world, which set a new direction for mobile technology. However, the technological revolution also has its negatives. Due to the large number of used materials for making smartphones, their environmental impact is definitely not negligible. Raw materials for smartphones are mined worldwide. However, the very manufacture of smartphones leaves the biggest carbon footprint - up to three quarters of the total emissions of the smartphones industry. In addition, the Greenpeace report (a non-governmental non-profit organization for environmental protection) suggests that the "smarter" phone you have, the more carbon footprint it leaves. Because of the average life cycle of two years, smartphones are essentially disposable.

The problem is that 85% to 95% of all carbon dioxide emissions in the first two years of using a smartphone is the production of a new mobile phone. In particular, the extraction of rare elements that every smartphone contains. In any case, by simply extending the use of the smartphone to 3 years, the carbon footprint will be greatly improved by avoiding the need to extract other rare elements. This is an important environmental knowledge.

In reality, however, servers and data centres are the largest source of carbon dioxide emissions, generating 45% of emissions within the sector by 2020. This is because every Google search or every Facebook download needs to process your computer. However, smartphones also play an important role here, as they are mobile applications that make us increasingly need non-stop running servers.

On the other hand, the use of smart phones plays an important role in economic growth and sustainable development. For sustainable development, technologies that provide open access to information are important.

The Czech Republic has for a long time been included among those European Union States with a high share of mobile networks traffic. It is just forecasting of the mobile networks traffic volumes, in the interconnection services (national and international services) in particular, what this study is dealing with. Mobile phone services and mobile phones, in particular in Indonesia, were analysed by Rafiy and Adam (2016).

For decision-making activities in any area, the quantitative information knowledge is a necessity. The quantitative information - its acquisition, transformation, transmission and use - is crucial also in the sustainable development process at all levels of decision-making in a wide variety of areas and forms. This decision-making process takes place at different geographical scales: municipalities, regional, national and international. However, decision-making at the level of smaller units is also important. The development of rural space plays a very important role in the European Union (and not only in the EU). Rural development policy affects the various sectors of the European economy. The growth of education and information in society is based on the economic and social growth of European world society. The development and use of ICT plays a very important role here. One of the objectives of sustainable rural development is to reverse rural migration. Employment stimulation, equal opportunities and, last but not least, the response to the growing demands for quality of life, health, safety, personality development and leisure.

Currently it is practically impossible to set up important economic decisions in the developed countries missing the knowledge of the basic indicators past development. Great emphasis is laid on a thorough analysis of these indicators development. The phenomenon given not only can be analysed based on the past recorded values development but its future ways can be predicted from these, too. And this is why the current path of the time series has to be modelled somehow. There are a number of areas where it is needed to apply the modern time series analysis methods. The time series theory belongs, in the area of economic indicators in particular, among the most important quantitative methods.

Out of the methods employed in the univariate time series extrapolation forecasts making of various indicators most often, are the exponential smoothing models (Corberán-Vallet et al., 2011; Billah et al., 2006; Gardner, 2006; Nimesh et al., 2014), thanks to the robustness (Cipra, 1992; Gelper et al., 2010) and simplicity of these in particular. Time series modelling and forecasting using the exponential smoothing techniques was the objective of Murat et al. (2016), too, who employed the techniques on time series data from the area of meteorology. Papic-Blagojevic et al. (2016) applied the exponential smoothing models on time series from the tourism area in Serbia, where the RMSE and BIC assessment criteria were exploited in the comparison of separate exponential smoothing models. Sbrana and Silvestrini (2014) dealt with the exponential smoothing methods problems and application of these in their study, from the area of wholesalers' inventories time series analysis in the USA. Like every method has ES also some disadvantages. Among them, there is the fact, too, that it cannot handle trends well. However, has also the advantages, such as, e.g., it produces accurate forecasts. Despite the noted shortages, the ES methods are very popular and they have been applied with success in many areas, the telecom area included. Gardner and Diaz-Saiz (2008) continued following their original work from 2006 by a new study aimed just at an analysis of indicators from the mobile telecommunications area. In particular, they dealt with the impact of cutting off a number of irrelevant older observations from the time series under study, upon the exponential smoothing models constructed quality. The Holt and damped trend methods were the objective of the study in particular. Lim et al. (2012) studied the possibility of 3G mobile subscription prediction in separate Chinese provinces, with regard to regional differences.

There are several ways of solution of univariate time series forecasting. Besides the classical trend models and adaptive models the Box-Jenkins methodology can be applied (Hindls et al., 2000). The BJ methodology is one of the modern approaches to time series analysis. It was presented in 1970 by the authors G. E. P. Box and G. M. Jenkins in their work „Time Series Analysis, Forecasting and Control“. They formed the theory and methodology for time series forecasting using the so-called ARIMA models – autoregressive integrated moving average models. The main merit of theirs is setting up the principles practically applicable, e.g., in situations where the „classical“ time series decomposition analysis fails.

Time series modelling and forecasting using the BJ methodology is widely exploited currently in various areas. Many authors have aimed in their studies at examining the ARIMA models in time series modelling and forecasting of various indicators. The ARIMA models have been applied with success in the telecom area, too. Bastianin et al. (2016) aimed in their study at the time series models selection strategy, incl. of the ARIMA models, and assessment of their appropriateness in time series forecasting of incoming calls on the telecom companies call centres. The forecast precision of this indicator can then in the companies facilitate reaching an optimal ratio between the operation costs incurred and the quality of services provided. Mastorocostas et al. (2012) prepared a study dealing with time series prediction of outgoing calls indicator within the University campus, using neural networks combined with fuzzy systems. Then they made a comparison with the well-known exponential smoothing models and the ARIMA models. A study with a very similar aiming was pre- pared by Hilas et al. (2006) who used the methods of seasonal decomposition, exponential smoothing and seasonal ARIMA models in forecasting national and international calls within the University campus. Actual data then were compared with 95 % confidence intervals constructed. Guo et al. (2009) dealt in their work with mobile networks traffic forecasting, using data supplied by China Mobile Communications Corporation (CMCC) Heilongjiang Co. Ltd., using the BJ methodology, seasonal ARIMA models in particular. Christodoulos et al. (2010) aimed in their research at improvement of the forecasts by a combination of two forecasting methods, see, the BJ methodology and the diffusion models. They applied the methods on time series concerning world broadband and mobile telecommunications´ penetration. Mastorocostas et al. (2014) in their work dealt with application, analysis and forecasting of time series from telecom area, where the fuzzy modelling method was applied in the studied indicators forecasting. They presumed in that work that, the model construction process is a two-phase one, where the first stage is Subtractive Clustering (SC) and then Orthogonal Least Squares (OLS) techniques follow. Findley (2005) has dealt with modelling and forecasting using the ARIMA models in general. Both methods (ES and ARIMA models) have also been used in the study by Hloušková et. al. (2018) or by Svatošová and Köppelová (2017).

In time series analysis and time series forecasting processing proper, a certain sequence of stages has been recommended and considering these, our research has prevalently been aimed at the stage of design of appropriate candidates for the modelling and extrapolation forecasts making purposes and the assessment of these, based on the assessment criteria selected.

The main aim of this work has been to perform a comparative analysis of the exponential smoothing models with the models provided by BJ methodology, and an applicability assessment of the time series models selected for past development modelling of selected indicators and for the traffic forecasting purposes in mobile networks. Subsequently we experimented with combined forecasts constructed based on a combination of both the methods analysed. Those models were combined which had been selected as the best ones in both the model groups based on the assessment criteria chosen. Data for application have been collected on monthly and daily basis and provided by the Vodafone Czech Republic, Ltd. company. In particular, these are data on traffic in the interconnect and roaming areas (national and international voice services, MMS, SMS, etc.)

Traffic forecasting in the area of mobile telecom services provision is very important for the telecom company. In this area (and not only here) no one has dealt so far with combined fore- casts construction supplying aggregated information obtained from the individual models, entering the aggregation. Wei and Yang (2012) have dealt with the forecasting methods combinations, too. Empirical studies by some authors signal promising results in the forecasts using combined methods, hence certainly it is significant to examine these chances. Contemporary methodology of time series analysis and forecasting has been developed very intensively over several recent decades and completed by new, often very sophisticated procedures, and with modifications of existing techniques. Practical applicability of these procedures has to be repeatedly and systematically verified and examined on real time series, since the time series models do not have a universal or permanent nature and have to be constructed in accordance with the properties of the indicators studied.

Materials and methods

Specification of analysed indicators and used statistical software

All in all, 72 short-term time series from the mobile telecom services have been exploited, out of which 44 daily frequency series (series of interconnection traffic – national voices services, international voice services, SMS and MMS services national and international, some special national voice services e.g. ATX services, coloured lines, emergency calls) and 28 series with monthly frequency of data collection (series of roaming traffic – voice, SMS, MMS and data services). Time series forecasting for telecom area based on daily data collection has been dealt with, e.g., by Mabert (1985), who analysed time series of numbers of calls on emergency lines.

Within this study, time series have been analysed with differing length of reference period, ranging from 89 to 273 data. Data proper on the indicators under study, i.e., the traffic volume in mobile networks, have been provided by Vodafone Czech Republic, Ltd. company.

Processing proper of the time series analysis of the indicators under study has been performed using the Time Series Forecasting System (TSFS) being a component of the SAS programme system. A part of the TSFS is the regime of automatic model selection capable of considerable acceleration of the optimal model search process for the time series analysis. The search process relies on diagnostic tests done, aimed at establishing the presence of trend, seasonality or need of logarithmic data transformation.

Time series modelling

Each of the time series studied was first automatically identified and diagnosed by means of the SAS system selection criteria. Then the 5 best models from the wide range of exponential smoothing models (adaptive models) and ARIMA models were constructed for each time series.

Based on models selected, a comparative analysis has been performed of both the model groups (the exponential smoothing models and the BJ methodology based models), considering differing frequencies and the two differing stages of time series analysis - interpolation and extrapolation.

In time series forecasting then the adaptive models have been applied with success, assuming that, for a future development extrapolation forecast construction the latest time series observations are those most valuable. Therefore, those will be assigned the highest weights and the older data either can be quite excluded from study or, they will be assigned lower weights as compared with the values obtained later. Hence, the adaptive models take aging of information into account. The weight system is formed by means of the so-called levelling constants assuming values from $< 0; 1 >$ interval. In order to find the optimal levelling constant value, the „method of trial and error“ has been applied in practice. As the optimal value such value can be chosen, which minimizes the error of estimate properly selected. The SAS statistical system, considered to be applied in this paper for efficient materialization of all the analyses needed, offers an automatic estimate of the levelling constant value.

The ARIMA models are very flexible and they can adapt quite quickly to changes over the time series. Therefore, the BJ methodology can, in particular, offer a starting point for modelling of a seasonal time series with a complex stochastic structure. In the real world there are many time series where the classical analysis models fail. The BJ methodology models just can be applied many times with success in such cases (Cipra, 1986).

Combined models

The SAS programme system is taken as one of the most perfect and most comprehensive statistical programme packets which satisfies conditions of this study, i.e., to have a really wide circle of various models available. The TSFS component facilitates construction of combined models both in the form of simple arithmetic average or weighted arithmetic average with differing weights. In our case, weighted arithmetic average has been chosen with the so-called regression weights offered, that can penalize somehow the forecasts loaded with higher forecast errors. At the same time, it is possible to aggregate the forecasts based on arithmetic averages of the original time series values of the indicators studied, or using arithmetic average of logarithms of those original values.

Assessment of models

Within many researches, the autocorrelation charts (ACF) and the partial autocorrelation functions (PACF) have been employed in order to identify best models (Mirzavand and Ghazavi, 2015). Applicability of most the time series analytical models namely depends on satisfaction of the assumption that, many of the residuals is of the so-called White noise nature, which is an uncorrelated random quantity with zero mean and constant variance (Seger and Hindls, 1993). Dissatisfaction of the assumption presents a signal for certain data modification, e.g., an adequate transformation. The ACF and PACF charts offer one of the ways for quality assessment of the time series models but it is not the only one. Just vice versa. The graphical analysis mentioned always should be completed by other tools.

In this paper of ours, the quality of models constructed has been assessed using the MAPE metric (Mean Absolute Percent Error) defined as:

$$M.A.P.E. = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{y_t - y'_t}{y_t}\right| \qquad (1)$$

where y_t or y'_t (t = 1, 2, . ., n) are the actual or the smoothed values of the given time series and n is the number of time series observations. Popularity of the MAPE metric use is based on its percentage expression. It is a dimensionless measure which facilitates mutual comparison of models constructed for different indicators.

Another convenient tool used in this work in order to acknowledge appropriateness of the models selected is the AIC (Akaike´s Information Criterion) defined as:

$$AIC(k) = n\ \ln(MSE) + 2 \qquad (2)$$

where n is the number of observations, k is the number of parameters (Bozdogan, 2000; Mirzavand and Ghazavi, 2015) and MSE is the Mean Square Error:

$$M.S.E. = \frac{1}{n}\sum_{t=1}^{1}(y_t - \hat{y}_t)^2 \qquad (3)$$

where y_t or y'_t (t = 1, 2, . ., n) are the actual or the smoothed values of the given time series and n is the number of time series observations.

The MAPE metric has been widely applied in quality assessment of the time series models constructed. For time series modelling and forecasting from the telecom area it has been used for model quality assessment by Mastorocostas and Hilas (2012), or Gardner (2006). Paul et al., (2015) used MAPE for the forecasts assessment of commodity prices in Mumbai market. The best forecasting model for the indicators studied was chosen based on the minimal AIC value.

The information criteria, among which the AIC belongs, inter alia, too, are also applicable in time series models assessment. They are applicable both for the exponential smoothing models and for the ARIMA models as well, where they find a wider use (Gardner, 2006). The Akaike information criterion was used by Ghosh et al. (2010) in the assessment of Functional-coefficient autoregressive (FCAR) model. They applied the FCAR model in modelling and forecasting of annual export lac data in India. AIC was, among others, object of a study done by Billah et al. (2006). They aimed at selection of exponential smoothing methods for time series forecasting from the area of the M3 forecasting competition. They studied 3 different approaches to the forecasting methods given selection. One of those is the approach, too, based on information criteria, such as the AIC. Bolin et al. (2015) have predicted the global sea level in their work employing the ARIMA model where the best model choice was done based on the AIC.

Results and discussion

Comparative analysis of exponential smoothing models and ARIMA models

The Table 1 shows clearly the percentages of success of both the two model groups. Considering the time series periodicity the table tells us - according to the chosen criteria - at what percentage share a model from the exponential smoothing models group ranked first and at what percentages the BJ methodology models ranked first. In this part of the paper both models for the purpose of past development modelling of the indicators under study have been constructed and assessed (interpolation) as well as models for forecasting of these (extrapolation).

It can be seen from the results obtained that, for the indicators selected concerning the numbers of minutes spent in the area of mobile telecommunications, the exponential smoothing models have been applied more often. It means, at both the stages of time series analysis, interpolation and extrapolation. Not even periodicity of the time series under study affects the comparison results of the two model groups. Based on the MAPE and AIC criteria values assessment the exponential smoothing models

INTERPOLATION			
Type of model	Daily time series	Monthly time series	TOTAL proportion
ARIMA models	38.64 %	10.71 %	27.78 %
Exponential smoothing models	61.36 %	89.29 %	72.22 %
TOTAL	100.00 %	100.00 %	100.00 %
EXTRAPOLATION			
Type of model	Daily time series	Monthly time series	TOTAL proportion
ARIMA models	50.00 %	17.86 %	37.50 %
Exponential smoothing models	50.00 %	82.14 %	62.50 %
TOTAL	100.00 %	100.00 %	100.00 %

Source: Own processing based on data provided by Vodafone Czech Republic, Ltd.

Table 1: Percentage representation of models placed on the 1st place.

have presented themselves as more appropriate for the past development description at roughly 72 % and for the given indicators forecasting at about 63 %. An outstanding difference in applicability between the two model groups has been recorded in monthly time series. At the interpolation stage in particular, where the exponential smoothing models have been found more appropriate of 89.29 %. An interesting outcome has been reached when comparing the groups as to the extrapolation properties assessment where the two model groups have been represented at the same share.

Assessment of the two model groups

In the Table 2 the model groups under study have been assessed using a selected MAPE metric. Table 2 shows the absolute model number in the ARIMA model group and the exponential smoothing model group with the MAPE indicator value reached, the values of which have been expressed in interval, for greater clarity. The results have been subdivided moreover according to the fact whether the model was applied in the indicator studied past development modelling or in its extrapolation.

It is seen from the results obtained that, within both the model groups in most cases MAPE values lower than 15 % have been reached, what is expressing quality of the models for use in the time series studied analysis. The MAPE metric values moved most often within 5 - 10 % interval or, they reached values lower than 5 %. There is no borderline generally accepted for the MAPE measure. In practice it is possible to meet varying situations and the MAPE value (its height) moves just depending on the actual situation. It is possible to meet a situation where a 5 % value is required, in another case 15 % again, nevertheless a model with MAPE value about 10 % can be taken as the suitable one. The outcomes obtained show that, in the ARIMA models group the MAPE values of the models constructed fluctuated within the desirable interval up to 10 % at 78.7 %, in the exponential smoothing models group the share was 69.1 %.

The AIC criterion served an additional measure in order to confirm suitability of the models constructed, the values of this corresponded to the MAPE values in almost 97 % cases. This means, the model chosen based on the lowest MAPE value could have been constructed for the time series given, in 97 % cases according to the AIC criterion, too. Here it holds again that, a model of higher quality can reach a lower value of this assessment criterion, too.

The Table 3 is presenting an overview of the best models in the separate model groups, those having been applied in the time series analysis under study most often, again considering the two time series analysis stages – interpolation and extrapolation. Besides the model names proper, Table 3 is providing information on how many times the given model has been chosen into the group of the five best ones – position of the separate models chosen in absolute view but in the relative (percentage) share, too.

The Table 3 presents the models most often employed within a more extensive research, where always five models were selected for each time series and time series analysis stage, for the following experiment with combined models construction. These were further exploited in the construction of the aggregated forecasting models, dealt with in the following chapter.

As it concerns the models situated always on the first place, then at the interpolation stage mostly the ARIMA (0,1,1)s NOINT and the Log ARIMA (0,1,1)s NOINT from the BJ methodology model group placed themselves (of the indicators

TYPE OF MODEL	INTERPOLATION	EXTRAPOLATION	TOTAL (both analysis)
	Count of models		
ARIMA Total	20	27	47
smaller than 5	2	20	22
between 5 and 10	10	5	15
between 10 and 15	3	2	5
higher than 15	5		5
Exponential smoothing Total	52	45	97
smaller than 5	11	23	34
between 5 and 10	20	13	33
between 10 and 15	11	4	15
higher than 15	10	5	15
Grand Total	72	72	144

Source: Own processing based on data provided by Vodafone Czech Republic, Ltd.

Table 2: Assessment of the models and specific MAPE values.

INTERPOLATION	TOTAL absolute number	TOTAL Proportion in %
ARIMA models - total	135	37.50%
ARIMA (0,1,1)s NOINT	18	5.00%
Log ARIMA (0,1,1)s NOINT	14	3.89%
Log ARIMA(0,1,2)(0,1,1)s NOINT	13	3.61%
Log ARIMA(2,1,0)(0,1,1)s NOINT	12	3.33%
ARIMA (2,0,0)(1,0,0)s	9	2.50%
Log ARIMA(2,1,2)(0,1,1)s NOINT	9	2.50%
Exponential smoothing models - total	225	62.50%
Seasonal exponential smoothing	34	9.44%
Log Winters method additive	27	7.50%
Log Winters method multiplicative	23	6.39%
Log seasonal exponential smoothing	22	6.11%
Seasonal dummy	20	5.56%
EXTRAPOLATION	**TOTAL absolute number**	**TOTAL Proportion in %**
ARIMA models - total	139	38.61%
ARIMA (0,1,1)s NOINT	21	5.83%
Log ARIMA(2,1,0)(0,1,1)s NOINT	15	4.17%
Log ARIMA(0,1,2)(0,1,1)s NOINT	12	3.33%
ARIMA (2,0,0)(1,0,0)s	11	3.06%
Log ARIMA (0,1,1)s NOINT	9	2.50%
Exponential smoothing models - total	221	61.39%
Seasonal exponential smoothing	30	8.33%
Log seasonal exponential smoothing	20	5.56%
Seasonal dummy	19	5.28%
Log Winters method multiplicative	17	4.72%
Log Winters method additive	15	4.17%

Source: Own processing based on data provided by Vodafone Czech Republic, Ltd.

Table 3: Overview of the best models.

collected on daily basis) and the Log ARIMA (2,1,0)(0,1,1)s model (indicators with monthly frequency). Out of the group of exponential smoothing models then these were the Log seasonal exponential smoothing and the Log Winters method additive models, on both the daily and monthly frequency time series.

The outcomes of this empirical research confirm the importance of extensive work aimed at detailed analysis of the exponential smoothing models. Gardner (2006) performed a detailed research in his work, where he started from an assumption that, the exponential smoothing methods are suitable and optimal for a very general class of models, which is wider than the ARIMA models class.

Construction and assessment of combined models for the indicators studied forecasting

For most of the individual models selected results have been obtained differing from both the MAPE and AIC criteria only slightly. Therefore, construction of aggregated models was included in the analysis and subjected to experimentation, too. Analysis was limited at the aggregated models construction aimed at the extrapolation of indicators studied. Combined models were constructed always of two best individual models. Combined forecasts have been obtained for the separate time series with MAPE values as given in Table 4.

The Table 4 shows the success rate of combined models based on the MAPE metric values. The MAPE measure values are grouped into 4 groups for better presentation, same as in the Chapter 3.2. However, the success rate here is expressed in percent.

For a better comparison of the combined models with the individual models see the following table.

The Table 5 is presenting the rate of success of individual models (placed on first places) in %, based on the MAPE metric values. It is obvious from the results presented that, the combined models indisputably have got properties appropriate for the time series under study extrapolation. The quality of these exceeds the individual models chosen as the best ones for each indicator on basis of their diagnostic testing results. The results in Tables 4 and 5 show that, combined models can be successfully applied in forecasts construction of the indicators studied. MAPE values lower than 5 % have been reached for these in 63.9 % cases, regardless of the indicators´ periodicity. Such low values were obtained for the individual models constructed, all in all, in 59.7 % cases.

Regarding periodicity of the indicators collected, the combined models assessed using the MAPE criterion have shown themselves more appropriate both on basis of the indicators collected monthly (the 5% limit has not been exceeded in almost 54 % cases), as well as the indicators collected on daily basis (the 5% limit has not been exceeded in 70.5 % cases).

Table 6 offers a clear information in how many % cases the combined model, eventually the individual model is more suitable for forecasting as assessed by the MAPE measure value.

Regardless of periodicity of the indicators studied, the combining technique of the individual forecasting models has shown itself a step in the right direction. Overall, the combined models have reached lower MAPE values in almost 70 % cases.

COMBINATION of 2 best models	peridodicity		TOTAL proporition in %
	daily	daily	
MAPE value - smaller than 5	70.45%	53.57%	63.89%
MAPE value - between 5 and 10	13.64%	32.14%	20.83%
MAPE value - between 10 and 15	9.09%	7.14%	8.33%
MAPE value - higher than 15	6.82%	7.14%	6.95%
TOTAL	**100.00%**	**100.00%**	**100.00%**

Source: Own processing

Table 4: MAPE values of the combined models.

INDIVIDUAL MODELS	peridodicity		TOTAL proporition in %
	daily	monthly	
MAPE value - smaller than 5	65.91%	50.00%	59.72%
MAPE value - between 5 and 10	18.18%	35.71%	25.00%
MAPE value - between 10 and 15	9.09%	7.14%	8.33%
MAPE value - higher than 15	6.82%	7.14%	6.94%
TOTAL	**100.00%**	**100.00%**	**100.00%**

Source: Own processing

Table 5: MAPE values of individual models placed on the first places.

Evaluation	peridodicity		TOTAL proporition in % (monthly and daily time series)
	model proportion in % - daily time series	model proportion in % - monthly time series	
combination is better	65.91 %	75.00 %	69.44 %
individual model is better	34.09 %	25.00 %	30.56 %
TOTAL	**100.00 %**	**100.00 %**	**100.00 %**

Source: Own processing

Table 4: MAPE values of the combined models.

A more detailed examination of the combined forecasts has to be materialized by experimenting. It is possible to experiment with a varying number of models entering the evaluation, length of the reference period or distance of the forecast horizon.

Conclusion

No single designer, company, or government can solve the carbon footprint of contemporary technology. However, significant environmental savings can be made, among other things, by both mobile operators (such as fuel savings on business trips or by reducing gas and electricity consumption) and by consumers, i.e. individuals. They can try to save the environment, or energy, while using a mobile phone. Just follow a few basic principles.

However, mobile phones and mobile telecommunications services can help unlock the potential of rural areas and make them more attractive places to live, as well as providing high-quality internet access. Information and communication technologies and their efficient use, facilitated by better high-speed internet access, are generally considered to be a key factor for increasing productivity and fostering innovation also in rural areas.

Outcomes of the research done confirm that, both the model groups having been the objective of study, can be successfully applied in modelling and forecasting within the domain of mobile telecom services use. However, the exponential smoothing models have recorded a more frequent application in the analyses done than the ARIMA models. What concerns frequency of the data collected, the exponential smoothing models have been found better applicable both for monthly and daily data, be it at the stage of interpolation or extrapolation, as well.

Based on the analysis done, the exponential smoothing models can only be recommended for the analysis of indicators under study from the mobile telecom area. The contemporary statistical programmes facilitate construction of not only the high quality individual forecasting models but combined models, too. The practice of combination techniques has brought about very good outcomes in prognosticating. Christodoulos et al. (2011) have assessed these techniques as very beneficial ones. Deb et al. (2017) have reached a conclusion, too, in their study that, the combined techniques are much more efficient in time series forecasting. They have dealt with construction and assessment of the combined models in the buildings energy consumption. Tavakkoli et al. (2015) have applied a combination of two models from the adaptive models class in their study – specifically the Double and Holt-Winters exponential smoothing models – with the ARIMA models, and they have assessed the benefit of this approach for particleboard consumption in Iran. The outcomes of this study also confirm that, the combined techniques are more efficient and they supply better results in the mobile networks traffic forecasting. In spite of the comparatively irregular ways of development of some of the indicators under study, both the individual and combined models employed here have been subject to rather low errors of prediction.

The research could continue further towards empirical analysis of a still more extensive time series collection, experimenting with varying lengths of the reference periods or the forecasting horizons, too. Madden and Tan (2007) too, have aimed at time series forecasting from the domain of telecommunications using linear models and experimenting with varying lengths of the forecasting horizons. In their study they reached a conclusion that, for longer (more distant) forecasting horizons in case of monthly time series, the exponential smoothing models are more fitting compared with the ARIMA models, the Holt exponential smoothing model in particular. Fildes et al. (1998) compared in their study various forecasting methods, incl. of the ARIMA models, considering precision of the prognoses constructed for different forecasting horizons and they reached a result that, the ARIMA models can set up more precise extrapolation forecasts for longer forecasting horizons – up to18 periods in advance.

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