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STATISTICAL ANALYSIS OF DEMAND FOR TELECOMMUNICATIONS SERVICES FOR FORECASTING PURPOSES – STUDY OF THE IMPACT OF FACTORS NOT ARISING FROM THE CALENDAR

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ABSTRACT

The aim of this study is to identify the impact of factors (not arising from the calendar) on the demand for connection services offered by a telecommunications operator. The theoretical part of the research presents the importance of the Prediction System (PS) as a kind of Decision Support System in the operational management of the telecommunications operator. Theoretical aspects of PS structure have been included. Special attention has been paid to the statistical analysis module (as the PS subsystem), which was implemented in the adopted (researched) scope in the empirical part of the research. The empirical part presents the results of statistical analyses of demand for telecommunications services in the scope enabling identification of the impact of factors not arising from the calendar (i.e. the impact of category of connection and type of subscribers) on the level and distribution of such demand. The presented research results provide premises for the construction of forecasting tools, carrying out the forecasting procedure and monitoring the forecasts, i.e. they provide the necessary premises for the implementation of subsequent components of the PS.

Key words: Prediction System, telecommunications operator, subscriber group, category of connection
JEL codes: C46, C53, D24

INTRODUCTION

Telecommunications operators deal with increasingly demanding competition. This fact makes it necessary for operators to continuously improve their decision-making processes. Keeping competitiveness and market existence on the telecommunications market is strongly connected with the quality of decisions made by the management staff. However, the quality of these decisions, depends on the reliability of the analyses carried out and the accuracy of forecasts of demand for telecommunications services of the com-

pany. Improvement of decision-making processes is based on the use of more and more effective Decision Support Systems (DSS), which enable decision making based on reliable premises and, as a consequence, reduce the level of uncertainty. One of the types of DSS is the Prediction System (PS) used for the analysis and forecasting of telecommunications traffic. A very important part of the PS is a multi-sectional statistical analysis of data, the main aim of which is to identify all factors having a statistically significant impact on the volume of telecommunications services provided. The results of statistical analyses form the

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basis for the construction of forecasting tools, which are based on the identified relations. Other elements of the PS are, among others, a prognostic database, statistical preprocessing of data, forecasting methods [Dittman 2004].

The PS supports operational planning [Daft and Marcic 2011, Griffin 2015]. In this context, the PS provides telecommunications operators with premises for price calculations, financial planning and effective network management. S. Kasiewicz [2005] pays special attention to operational management, indicating this level of management as the main decision-making field for managers, which strengthens the effectiveness of the growth of the company's value. On the other hand, M. Marcinkowska [2000] includes innovation, information and information system among the internal sources of company value. From this point of view, it is very important that the company's decision support procedures are innovative and effective. Nevertheless, telecommunications operators do not disclose their data mining techniques or their level of efficiency. Therefore, the issues of analysis of telecommunications traffic and its forecasting are not widely described in the literature and the knowledge transfer based on the experience of operators practically does not exist [Muraszkiewicz 2000].

The aim of the article is to identify the impact of specific factors (not arising from the calendar) on the level of demand for telecommunications services. Therefore, the demand surveys have been conducted in the categories of connections and subscriber groups (i.e. using classification factors not arising from the calendar). An hourly approach has been applied, which made it possible to analyse the daily courses of demand for telecommunications services of the telecommunications operator. The impact of calendar factors has been omitted, which include e.g. hour in a day, type of day (working day, Saturday, Sunday, holiday), month. Calendar factors constitute a separate and extensive group that would require separate analyses. The analyses carried out constitute suggestions for the implementation of one of the elements of the PS, i.e. statistical analysis of prognostic data. The obtained results of analyses provide premises for the construction of forecasting tools, as

well as broaden the scientific basis for the economics of telecommunications traffic in the given scope of demand for connection services.

The research material has been made available by one of the telecommunications operators. The data used in the analysis were the hourly totals (in seconds) of outgoing calls generated by a specific group of subscribers (business or individual), during a selected working 24 hours and within a specific category of connection (mobile networks, local internal, local external, inter-city, international, other). The empirical material with the structure described above covered one year.

The Prediction System (PS) of a company

The PS constitutes a subsystem of an information system. The company's information system is a spatially and temporally ordered collection of information, broadcasters and recipients of information, information channels and technical means of information transmission and processing. The functioning of the information system enables the management of the company. The effects of the PS are prospective information concerning the company's immediate and remote environment, as well as its internal characteristics.

The PS involves the following elements: prognostic database, methods of statistical data preprocessing, methods of statistical data analysis, forecasting methods, forecast monitoring system, computer programmes.

The marketing information system has a significant role in the creation of a prognostic database. Within this system, important external and internal variables of the company are specified and monitored, information is provided to enable the implementation of a proper strategy and the acquisition of data necessary to make forecasts. In the marketing information system one can distinguish: marketing research subsystem, internal registers and reports subsystem, marketing interview subsystem.

Marketing research is a procedure for obtaining and analysing new data. The research serve to make marketing decisions and collect specific data that is not routinely collected in other sources.

Internal data sources should primarily include: registers and reports routinely prepared by various organisational units of the company (e.g. sales department, financial department, production department, analysis department). These sources accumulate information on the company's internal characteristics (sales volumes, costs, receivables, liabilities, orders, etc.).

External data sources collect daily information about changes in the company's immediate and remote environment. Suppliers of such information include: legislator (acts, resolutions), government (documents, statements, programmes, international agreements, government contracts), international communities, suppliers, banks, advertising agencies, intermediaries, competitors.

The marketing information system collects the data which are stored in the form of an electronic database. The part of the database used to make forecasts is defined as a prognostic database. In the conducted research, a prognostic database (prepared on the basis of registers and reports on billing characteristics of a selected telecommunications operator) have been used. The database consisted of hourly counted seconds of outgoing calls from the period of the year in cross-sections of categories of connections and subscriber groups.

The methods of statistical preprocessing of prognostic data include methods of data transformation, data aggregation, and missing data completion.

Statistical analysis of forecast data is carried out, among others, through identification of the components of the time series, identification of relationships between the forecast variable and explanatory variables, measurement of similarity of variables and identification of unusual observations, i.e. influence observations or outliers. The analyses, which have been presented in the empirical part of the article, are included in the scope of statistical analysis of the PS data. The empirical part of this article proposes a way of using several statistical techniques to study the demand for telecommunications services.

Forecasting methods are an important element of the PS. The method of forecasting in the literature of the subject is understood as techniques of information processing describing the forecasting situation and the way of transition from processed data to forecasting, adjusted to the adopted forecasting principle. Within the most forecasting methods, information about the past is processed. Within the framework of the general forecasting principle, different methods of forecasting may be applied, which differ mainly in the way the information is processed [Makridakis et al. 1998; Kaczmarczyk 2017, 2018].

The PS should provide monitoring of forecasts, i.e. checking their accuracy. Monitoring is guaranteed by checking whether the forecasts are free and whether they fall within the tolerance range provided for them.

Presentation of data and research methodology

The measurable dependent (response) variable Y_i was the hourly sums of seconds of outgoing calls generate by a specific group of subscribers during a working 24 hours and within a specific category of connection. A total of 8 measurable dependent variables have been defined. The variables presented below are divided into two sets: set $A_1 = \{Y_1, Y_2, Y_3, Y_4, Y_5, Y_6\}$ and set $A_2 = \{Y_7, Y_8\}$. The studied variables are listed in Table 1.

The classification of variables presented in Table 1 resulted from the specificity of the conducted studies. Statistical analyses concerned first of all the impact of the subscriber category on telecommunications traffic in the understanding of the level of demand for telecommunications services, as well as the distribution of such demand. Subsequent analyses were devoted to the verification of the impact of the connection category on the studied demand in the same scope as above.

In order to carry out these analyses, it was therefore necessary to define the classification factors X for both sets of dependent variables. Table 2 summarises all classification factors and their levels.

The data included a total of $52 \cdot 24 \cdot 2 \cdot 6 = 14{,}976$ observations (52 is the number of all Wednesdays of the year, number 24 indicates hours per day, 2 concerns the number of subscriber groups, 6 is the number of analysed categories of connections). The course of the daily cycle of average demand for connection services in the system described above is presented in Figure 1.

Table 1. The set of all measurable dependent variables which have been used in research study

Variable marking	n	Variable name
		Set A_1
Y_1	2,496	Hourly combined seconds of outgoing calls to mobile network during working 24 hours
Y_2	2,496	Hourly combined seconds of outgoing calls during working 24 hours within the framework of local calls to the same network
Y_3	2,496	Hourly combined seconds of outgoing calls during working 24 hours within the framework of local calls to other network
Y_4	2,496	Hourly combined seconds of outgoing calls during working 24 hours within the framework of trunk calls
Y_5	2,496	Hourly combined seconds of outgoing calls during working 24 hours within the framework of international calls
Y_6	2,496	Hourly combined seconds of outgoing calls during working 24 hours within the framework of other connections
		Set A_2
Y_7	7,488	Hourly combined seconds of outgoing calls generated by business subscribers during working 24 hours
Y_8	7,488	Hourly combined seconds of outgoing calls generated by individual subscribers during working 24 hours

n – numbers of observations within the framework of a given variable. All Wednesdays from the period of a year represent a working 24 hour (52 Wednesdays), so 1,248 observations represent chosen category of connection in one group of subscribers (business or individual).

Source: Author's own coverage.

Table 2. The specification of all applied classification factors and their possible levels

Variable marking	Variable name	Possible values of the variable
	For variable belonging to set Y_1	
X_1	Kind of subscribers group	$x_{1,1}$ – business subscribers
		$x_{1,2}$ – individual subscribers
	For variable belonging to set Y_2	
X_2	Type of connections category	$x_{2,1}$ – mobile networks
		$x_{2,2}$ – local calls to the same network
		$x_{2,3}$ – local calls to other networks
		$x_{2,4}$ – trunk calls
		$x_{2,5}$ – international calls
		$x_{2,6}$ – other connections

Variable name means classification factor. Possible values of the variable mean levels of classification factors.
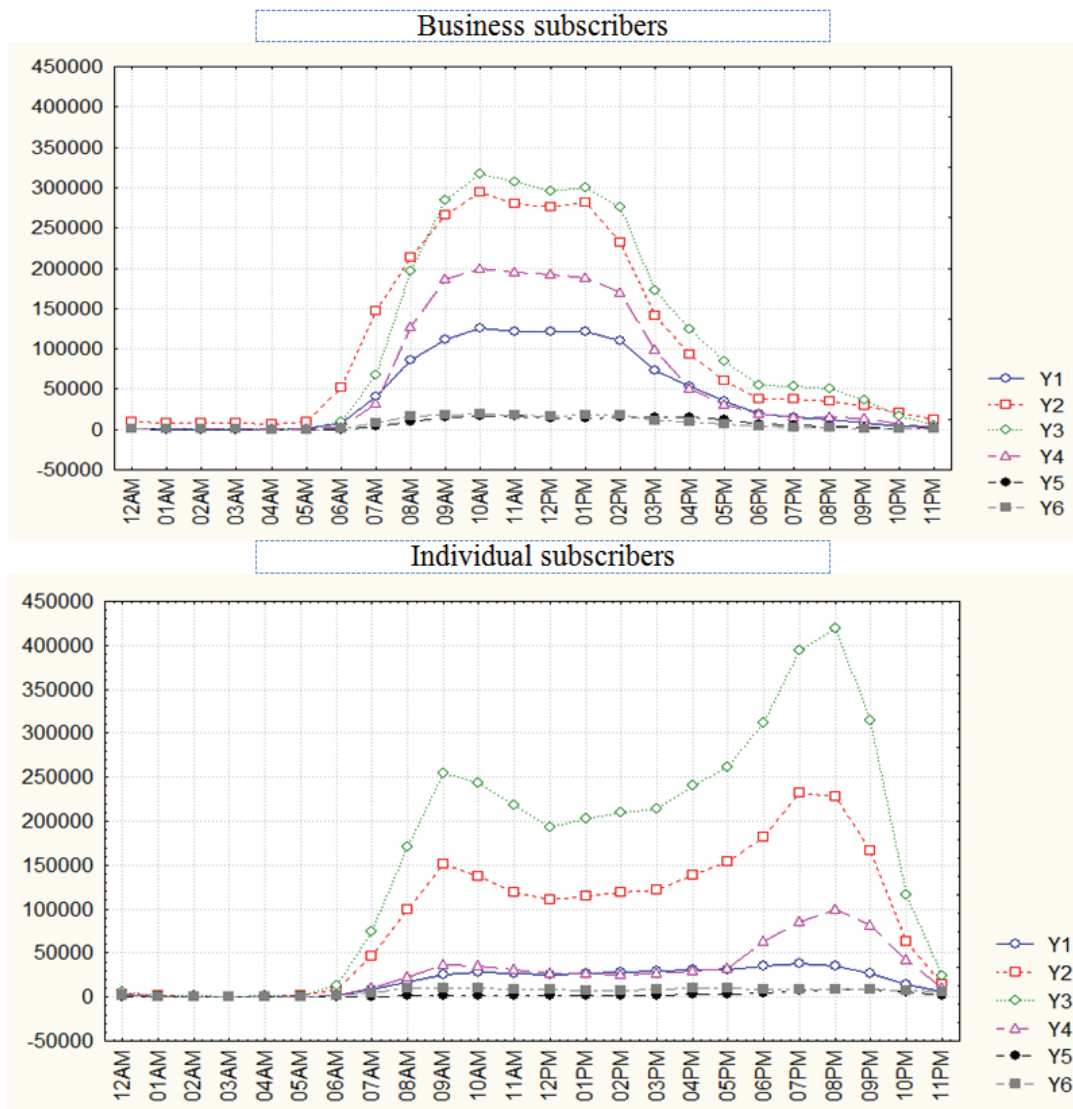
Source: Author's own coverage.

Fig. 1. The average time (sec.) of outgoing calls generated by business subscribers and individual subscribers in hours of working 24 hours

Source: Author's own coverage.

The structure of demand for telecommunications services (a categorised histogram with right-closed intervals) in the studied scope (i.e. during the working 24 hours, within 2 subscriber groups and 6 categories of connections) is presented in Figure 2.

In turn, Table 3 presents a description of all analyses, the results of which are presented and discussed in the calculation part of this research study (i.e. in section 3 of the work). In analysis 1 and 2, the subscriber group acted as a classification factor i.e. as a non-measurable (qualitative) variable assuming two levels. As far as analyses 3 and 4 are concerned, the classification factor is a category of connection – a non-measurable variable assuming 6 levels. Therefore, the set A_1 was used in analysis 1 and 2, and the set A_2 was the basis for the analysis of 3 and 4. Parametric statistical
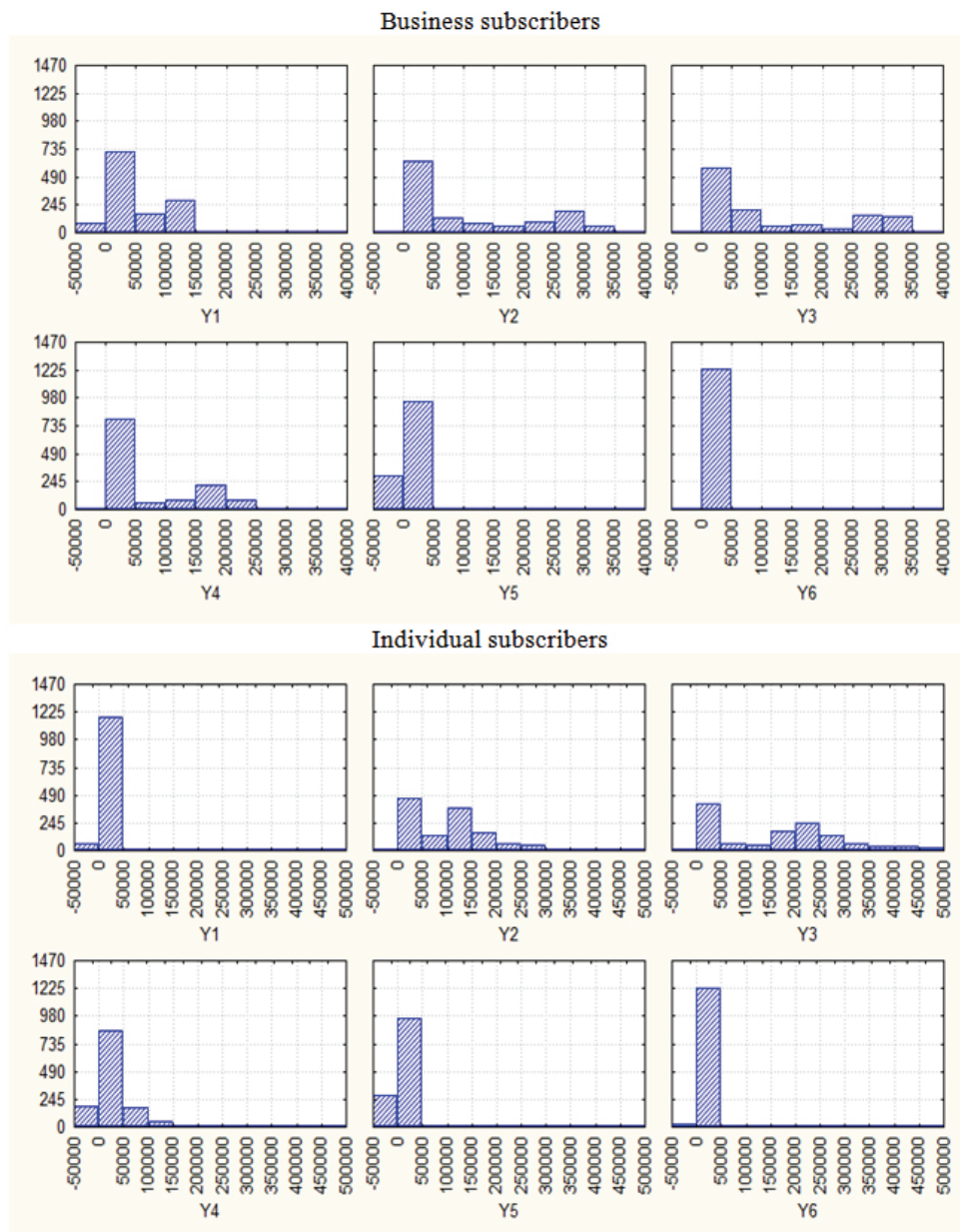
Fig. 2. The structure of observations (hourly counted sec.) of outgoing calls generated by business subscribers and individual subscribers during working 24 hours

Source: Author's own coverage.

tests (comparison of means and ANOVA) were used because for large populations ($n > 100$) parametric tests can be used instead of non-parametric tests, even though the tested variable does not have a normal distribution. This is possible due to the fact that the distri-bution of means from these populations is normalised [LeBlanc 2004; Black 2010; Healey 2012; Lee et al. 2013]. The power of parametric tests is higher than the power of non-parametric tests. The chosen tests are used when compared data are from two independ-

Table 3. Characteristics of the projected analyses

Analysis no 1–4	Aim of the analysis	Variable Y	Variable X	Statistical method
1	Identification of impact of subscriber group on the level of analyses demand	Set A_1	X_1	Z-test for the difference between the means
2	Identification of impact of subscriber group on the demand distribution of analyses demand			The Kolmogorov-Smirnov test
3	Identification of impact of connection category on the level of analyses demand	Set A_2	X_2	ANOVA test
4	Identification of impact of connection category on the demand distribution of analyses demand			The Kolmogorov-Smirnov test

Source: Author's own coverage.

ent groups (comparison of means) or three or more independent groups (ANOVA). An example of the application of these procedures is when an independent group of respondents attribute ratings to two or three or more products or services. Similarly, when the same product or service is assessed by two or three or more independent groups of respondents.

The Kolmogorov-Smirnov test was used to check the differences in the shapes of the distributions of two independent populations. The test was used to compare the shape of demand distributions in pairs of different categories of connection in the same subscriber group and to compare the shape of the distributions in pairs of the same categories in different subscriber groups.

Results of the study and discussion

The analysis 1 verified the hypothesis H_0 (for each variable of set A_1) that the demand for telecommunications services does not differ significantly between business and individual customers during a working 24 hours, i.e. the subscriber group has not a statistically significant impact on the level of demand for connection services. Assuming that there are two populations with normal distributions $N(m_1, \sigma_1)$ and $N(m_2, \sigma_2)$, the hypothesis H_0 has taken the following form: $H_0 : E(Y_{i, x_{1,1}}) = E(Y_{i, x_{1,2}})$, against the alternative hypothesis H_1 expressed as follows: $H_1 : E(Y_{i, x_{1,1}}) \neq \neq E(Y_{i, x_{1,2}}), i = 1, 2, …, 6$.

Z-test has been used for the difference between the means. The visual analysis indicates that the arithme-

tic means, as well as the standard deviations and variances of the two samples tested are numerically different for each connection category (Fig. 3). However (according to the remarks of Luszniewicz and Słaby [2008]) meeting the assumption of uniformity of variance is not a necessary condition for conducting the Z-test (as in the case of ANOVA).

Z-test results (for $p = 0.05$) for the two compared groups (business and individual) within the separately analysed categories of connections are presented in Table 4.

A region of rejection has been formulated $H_0 \in (-\infty, -1.6449\rangle \cup \langle 1.6449, \infty)$. The empirical values of the Z statistics are in this range. For each connection category, the hypothesis H_0 has been rejected. Therefore, there are clear reasons to reject the assumption that there is no impact of the classification factor on the variability of the dependent variable. The impact of the subscriber group on the demand for telephone services is statistically significant.

For each category of connection, another null hypothesis was then put forward, namely that the shape of demand distribution generated by two groups of subscribers during a working 24 hours do not differ (analysis 2). It was assumed $H_0 : F_1(Y_{i, x_{1,1}}) = F_2(Y_{i, x_{1,2}})$, regarding to $H_1 : F_1(Y_{i, x_{1,1}}) \neq F_2(Y_{i, x_{1,2}}), i = 1, 2, …, 6$. The results of the analysis are presented in the Table 5.

In the vast majority of cases analysed, there are statistically significant differences (empirical values of λ
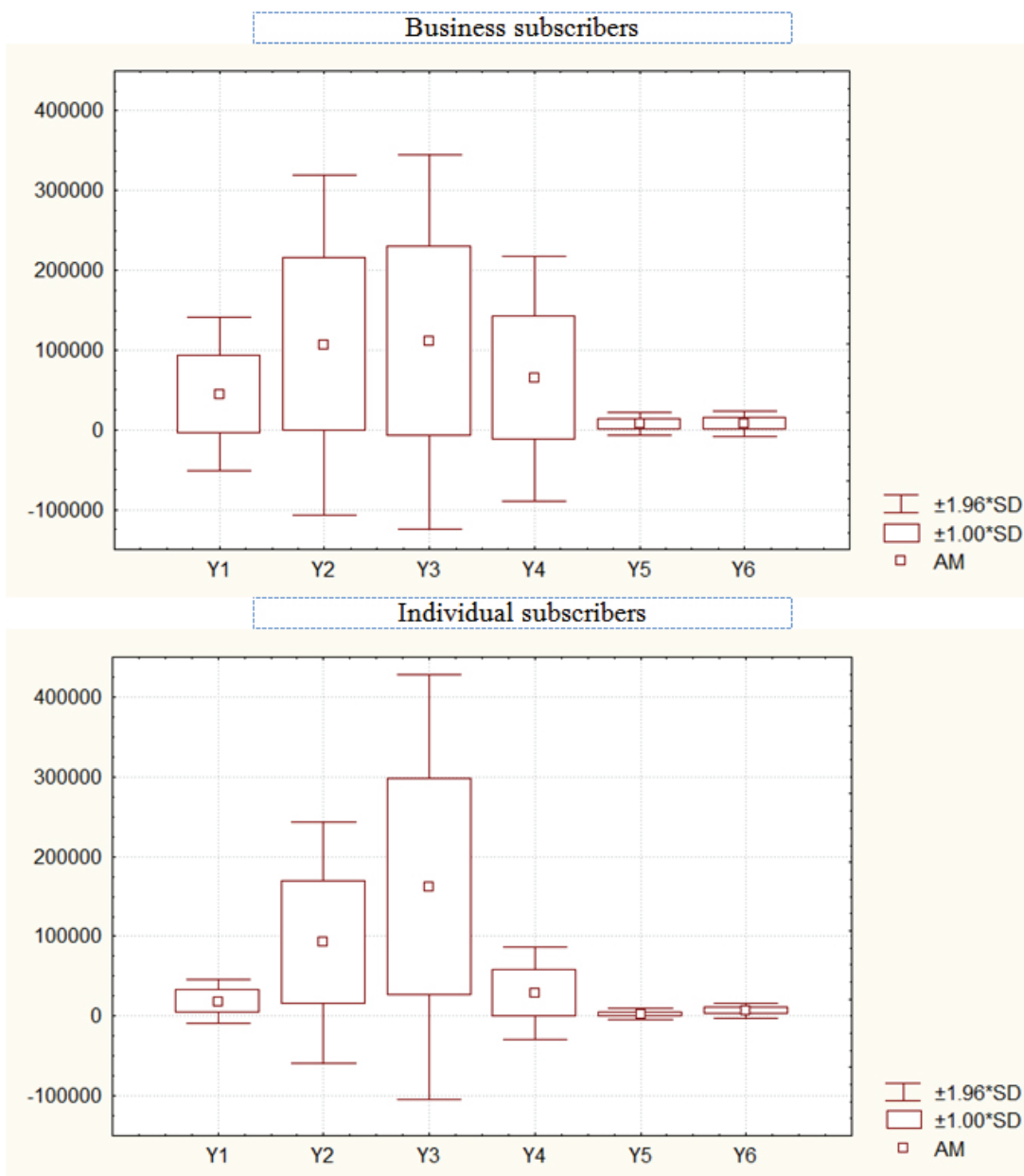
Fig. 3. Box-plots on the basis of demand for telecommunications services within the framework of particular category of connections and chosen group of subscribers

Source: Author's own calculations and coverage.

statistic are higher than the critical value $\lambda_{CV} = 1.358$ for $p = 0.05$). Differences were not found only for international and other calls.

Within the framework of analysis 3 of the study, there has been the hypothesis H_0 that the level of de-

mand for telephone services does not differ significantly from one connection category to another during a working 24 hours. Hypotheses H_0 and H_1 are as follows: $H_0 : E(SSB)_{Y_i} = 0$, $H_1 : E(SSB)_{Y_i} > 0$, where SSB – *Sum of Squares Between*, $i = 7$ or 8.

Table 4. Results of Z-test for the difference between the mean of demand generated by business subscribers and mean of demand generated by individual subscribers within the framework of consecutively analysed categories of connections (sec.)

H_0	$\bar{y}_{i,x_{1,1}}$	$\bar{y}_{i,x_{1,1}}$	Z	n	p
$E(Y_{1,x_{1,1}}) = E(Y_{1,x_{1,2}})$	44 641.3317	18 394.6394	18.1295	2 494	0.0000
$E(Y_{2,x_{1,1}}) = E(Y_{2,x_{1,2}})$	106 632.4183	92 139.1779	3.8315	2 494	0.0001
$E(Y_{3,x_{1,1}}) = E(Y_{3,x_{1,2}})$	110 864.1218	162 012.5369	−9.9709	2 494	0.0000
$E(Y_{4,x_{1,1}}) = E(Y_{4,x_{1,2}})$	64 583.5721	28 807.1058	15.0761	2 494	0.0000
$E(Y_{5,x_{1,1}}) = E(Y_{5,x_{1,2}})$	7 205.5385	2 540.0064	20.2881	2 494	0.0000
$E(Y_{6,x_{1,1}}) = E(Y_{6,x_{1,2}})$	7 323.9391	6 167.1667	4.3577	2 494	0.0000

$\bar{y}_{i,x_{1,1}}$, $\bar{y}_{i,x_{1,1}}$ – arithmetic mean for the business group and individual group respectively.

Source: Author's own calculations and coverage.

Table 5. Results of K-S test to compare distribution function of demand generated by business subscribers and distribution function of demand generated by individual subscribers in terms of consecutively analysed categories of connections (sec.)

H_0	D	λ	H_0	D	λ
$F_1(Y_{1,x_{1,1}}) = F_2(Y_{1,x_{1,2}})$	0.3638	9.0873	$F_1(Y_{4,x_{1,1}}) = F_2(Y_{4,x_{1,2}})$	0.2708	6.7654
$F_1(Y_{2,x_{1,1}}) = F_2(Y_{2,x_{1,2}})$	0.1899	4.7438	$F_1(Y_{5,x_{1,1}}) = F_2(Y_{5,x_{1,2}})$	0.0072	0.1801
$F_1(Y_{3,x_{1,1}}) = F_2(Y_{3,x_{1,2}})$	0.2460	6.1449	$F_1(Y_{6,x_{1,1}}) = F_2(Y_{6,x_{1,2}})$	0.0040	0.1001

D – the highest difference between the cumulative frequencies, λ – the empirical value of the test statistic.

Source: Author's own calculations and coverage.

Conditional means are characterised by (based only on Figure 1) clearly different values. The only exceptions are similar average call times for a pair of variables Y_5 and Y_6 (in both subscriber groups). Conditional variances and standard deviations are also differentiated and do not show a numerical regularity due to a decrease or increase in the levels of conditional means.

Calculated values of statistics F are clearly greater than the critical value of statistics $F_{0.05; 5; 7482} = 2.2153$. Therefore, there are clear grounds for rejecting the assumption that there is no impact of the classification factor (i.e. category of connection) on demand

volatility in the group of business subscribers and in the group of individual subscribers (Table 6).

Subsequently, for each pair of categories of connections, a null hypothesis (the shapes of demand distribution within a single subscriber group during a working day do not differ due to the categories of connections) was verified (analysis 4). It was assumed $H_0 : F_1(Y_{i,x_{2,k}}) = F_2(Y_{i,x_{2,l}})$, regarding to $H_0 : F_1(Y_{i,x_{2,k}}) \neq F_2(Y_{i,x_{2,l}})$; $i = 7$ or 8; $k, l = 1, 2,$ …, 6; $k \neq l$. In almost all pairs of data samples compared, the obtained empirical values of the statistics λ Kolmogorov's are higher than the critical value.

Table 6. Results of ANOVA test to compare level of demand generated in 6 categories of connections by particular group of subscribers.

H_0	MSB	s_1	MSE	s_2	F	p
$E(SSB)_{Y_5} = 0$	2 626 309 598 969.7	5	5 820 276 687.3	7 482	451.2	0.0000
$E(SSB)_{Y_6} = 0$	4 973 892 815 318.7	5	4 262 340 559.1	7 482	1 166.9	0.0000

MSB – mean square between; MSE – mean square error, s_1, s_2 – numbers of degrees of freedom.
Source: Author's own calculations and coverage.

This argues in favour of rejecting the hypothesis of equal distribution of collected measurements. So, the classification factor significantly differentiates the shapes of distributions of the examined populations. Differences were not found only for mobile and other calls in terms of individual customers.

CONCLUSIONS

The effective conduct of statistical analyses as a module of the PS is of great importance for the overall functioning of the PS. Statistical research on the demand for telecommunications services generated in individual (separately analysed) analytical cross-sections form the base, which is necessary for the implementation of subsequent PS modules. Such a database plays the role of a detailed image of demand for connection services at a selected time within a specific type of day (working day, Saturday, Sunday, specific holiday), a specific subscriber group (business and individual subscribers), connection category (e.g. mobile networks, internal local network) – i.e. it is the basis for the implementation of those PS modules, in which an appropriate forecasting tool is selected and forecasts are formulated. An effective PS supports the process of creating price lists of connections and network management, i.e. reduces the level of uncertainty in operational management processes.

The first two of the analyses described relate to the comparison of subscriber groups in terms of the level of demand and the shape of its distribution. The first of the described calculation procedures allows for positive verification of the thesis of statistically significant impact of the subscriber group on the variability of hourly demand during the working 24 hours within each analysed category of connection. The second analysis confirms the assumption that the shapes of demand distribution in the studied groups are statistically significantly diversified. Two further analyses are related to the comparison of categories of connections (in terms of level and distribution of demand) within one subscriber group. The results of the conducted tests clearly indicate that the category of connection is a factor which has a statistically significant impact on the level and distribution of demand for telecommunications services.

The obtained results indicate that all the factors adopted for analysis (not arising from the calendar) are of significant importance in constructing forecasting models. These results therefore provide information on important variables that are important from the point of view of forecasting model construction. The classification factors analysed should be included in the model as dependent variables (qualitative variables) if a multi-sectional model is the subject of the construction. The obtained results also suggest that the analysed demand can be modelled in one analytical section only, which would result in a single-sectional model. Due to the significant diversity of distributions, attempts to construct forecasting models based on specific distributions seem to be interesting as well. Such an approach would require tests to check the fit of the distribution in specific analytical sections (determined by statistically significant factors not arising from the calendar).

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ANALIZA STATYSTYCZNA POPYTU NA USŁUGI TELEKOMUNIKACYJNE W CELACH PROGNOSTYCZNYCH – BADANIE WPŁYWU CZYNNIKÓW NIEWYNIKAJĄCYCH Z KALENDARZA

STRESZCZENIE

Celem niniejszego opracowania jest identyfikacja wpływu czynników (niewynikających z kalendarza) na zapotrzebowanie na usługi połączeniowe oferowane przez operatora telekomunikacyjnego. W części teoretycznej pracy przedstawiono znaczenie Systemu Prognostycznego (SP) jako swoistego rodzaju Systemu Wspomagania Decyzji w zarządzaniu operacyjnym operatora telekomunikacyjnego. Zawarto teoretyczne aspekty budowy SP. Szczególną uwagę poświęcono modułowi analizy statystycznej (jako podsystemu SP), który w przyjętym (badanym) zakresie został zaimplementowany w części empirycznej pracy.

W części empirycznej zaprezentowano wyniki analiz statystycznych popytu na usługi telekomunikacyjne w zakresie umożliwiającym identyfikację wpływu czynników niewynikających z kalendarza (tj. wpływu kategorii połączenia i rodzaju abonenta) na poziom i rozkład tego popytu. Zaprezentowane wyniki badań dostarczają przesłanek do konstrukcji narzędzi prognostycznych, przeprowadzania procedury prognostycznej i monitorowania prognoz, tzn. dostarczają niezbędnych przesłanek do implementacji kolejnych elementów składowych SP.

Słowa kluczowe: System Prognostyczny, operator telekomunikacyjny, grupa abonencka, kategoria połączenia