Telecommunications Services Selection Process Based on Analysis of Services Adoption

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***Abstract*—Telecommunications operators continuously adapt their services offerings to new services usage trends in order to expand their customer base and enhance business models. With regard to existing services usage patterns, it is possible to select services that are suitable to users' needs and to create stronger business models. This is especially important given the fact that, despite numerous advantages arising from the new Internet of Things (IoT) solutions, a majority of operators still have not defined adequate IoT offers and related strategies for the deployment in the telecommunication markets. In this paper, the process of selection of telecommunications services is examined considering predictive modeling processes which are based on the time series data representing services adoption rates. The given forecasted results indicate an effective choice for creating adequate business models based on IoT services offerings and a reduction of modeling risks which are often related to the deployment of new services on the market.**

Keywords - telecommunications services; services usage; prediction models; business modeling.

I. INTRODUCTION

An overall boost in the volume of network traffic and the evolution towards the next generation networking based on advanced information and communication technologies (ICT) encourage telecommunications operators to consider and improve their existing business planning and modeling approaches according to market trends and services usage patterns in the existing network settings. Due to a vast number of possible options and existing requirements related to quality, efficiency, and performance of novel telecommunications services, an optimal selection of services becomes a very challenging task for operators. Although services quality will be additionally addressed by intelligent algorithms for adapting resource management and implementation of adequate techniques for content offloading, given accelerated trends in services development, there is often not a lot of time to closely consider customer requests related to services offerings before launching services on the markets. This last aspect is particularly important considering the fact that a vast number of operators are currently searching for the best solutions for positioning on the Internet of Things (IoT) services markets.

The prediction-based planning, services selection, and business modeling processes present significant challenges for operators under new market conditions. Therefore, the selection of adequate models for services offerings based on analytics of adoption of similar types of telecommunications services can effectively contribute to the optimization of business planning processes, as presented by analyses results gathered in this paper, as well.

Telecommunications services analytics usually takes into account time series data reflecting usage rates of particular services. That could point to valuable communication services, which reflect the specific needs of particular types of end users. If taking data representing services usage patterns into account to derive useful knowledge within a certain environment, suitable prediction models must be defined.

In this paper, the analytics of telecommunications services adoption processes is conducted using several predictive models which take into account only the cases with small sets of available time series data. In Section 2, an overview of current trends in telecommunication services adoption is presented. In Section 3, the importance of usage of the models for prediction of telecommunications services adoption in optimal business modeling is accentuated, and an overview of several common, as well as some additional predictive models, is presented. In Section 4, the defined models are applied to several collected data sets, and the collected results are presented and analyzed. In Section 5, in order to reduce the business modeling risks, optimal approaches in making decisions are indicated when short-term business planning is necessary under fast-changing market conditions.

II. TELECOMMUNICATIONS SERVICES ADOPTION TRENDS

The majority of current forecasts and market estimates reflect operators' high expectations for scale and scope arising from advanced telecommunications services offerings, and especially IoT services offerings. The positive expected results represent a major incentive for advanced services development and implementation processes. These expectations introduce new research challenges across different telecommunications settings.

The majority of businesses based upon usage of advanced telecommunications services monitor metrics that reflect improvements in supply levels and customer quality of experience rates. Higher levels of availability and quality of services could induce additional growth of services adoption, which is closely correlated with profitability gains, as presented in Figure 1 [1].

 ISBN: 978-1-61208-727-6

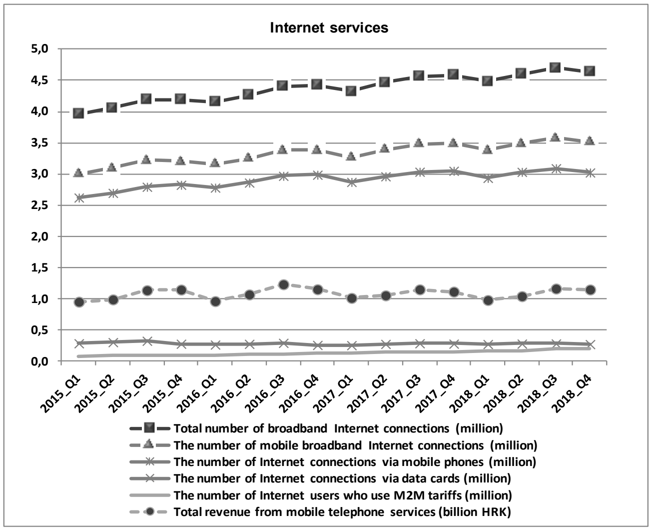


Figure 1. Internet services adoption rates and revenues.

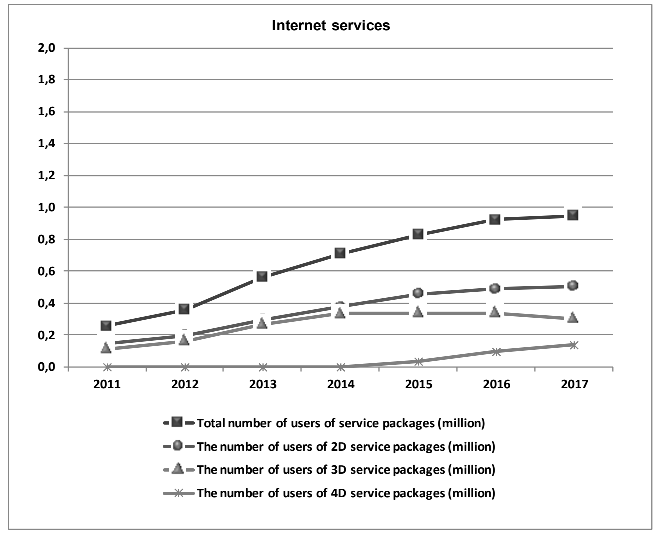


Figure 2. Internet services packages.

Therefore, the analyses and comparisons of possible business models involving various telecommunications services are important for the business planning processes of every telecommunications operator on the market since a timely application of relevant data and new knowledge represents an important advantage within every business modeling process, and can help in reducing churn rates.

Intensive adoption processes of a wide range of Internet services are currently taking place, as illustrated in Figure 1 [1]. One of the main drives behind the further anticipated traffic growth is the usage of audio and video-on-demand services and increase of the video content resolution [2]. So, audio-visual media streaming will account for the majority of overall network data traffic. In addition to these factors, other factors that are expected to impact the overall future traffic demand comprise an increase in the bit-rates and quality of experience. Moreover, the exchange of data traffic among end-user devices, terminal network equipment, servers and storage in the cloud will continue to grow.

The IoT solutions have the potential of becoming major contributors to the upcoming change in developing ICT business concepts. As part of the IoT solutions, Machine–to–Machine (M2M) services, which include automated communication and data transmission among two or more ICT entities, also have the potential of becoming one of the fastest growing segments for the Internet usage and increased mobile data demand. Although common characteristics of IoT and M2M are based on remote access to devices, IoT is expanding the concept of M2M because it can be integrated into comprehensive, scalable, and flexible business solutions. While IoT is focused more on software solutions and the IP network, M2M communication is predominantly oriented on embedded hardware and mobile networks. M2M communications are based on installing a SIM card or pulling a fixed line, but considering the fact that M2M with internet protocol represents a part of IoT, the common M2M/IoT services adoption trends can be closely analyzed.

As presented in Figure 2, many different forms of telecommunications services offerings are currently available in the markets [1]. Although the stand-alone service offerings have kept a strong position in the markets, services packages comprising more than one type of service have also achieved intensive adoption rates. These are, for example, any service packages where two (i.e., the 2D packages) or three (i.e., the 3D packages) electronic telecommunications services (e.g., the Internet, telephone or/and TV services) are provided to users jointly. The 4D packages, which have recently been introduced in the markets, mainly comprise a combination of telephone services in the fixed network, telephone services in the mobile network, Internet services, and TV services. As can be seen from the services adoption rates presented in Figure 2, the 4D packages note for fast adoption growth, mainly based on their total value. This goes in line with the concept which suggests the creation of all-inclusive services offerings for the end users, and a specific definition of the services' features [3].

Many advanced telecommunications networks implement necessary features that allow simultaneous management of various services, applications, and devices with different network and traffic requirements, and defined the quality of services. The methods that can be considered necessary for the selection of adequate services offerings to achieve optimal business models are based on the usage of predictive models and accurate forecast of services adoption rates.

III. PREDICTIVE MODELS

The models for prediction of telecommunications services adoption rates are increasingly important for optimal business modeling. The various predictive models whose implementation contributes to accurate business modeling are used [4].

 ISBN: 978-1-61208-727-6

An overall increase in network traffic has encouraged telecommunications operators to search for the best approaches to handle available data traffic, apply analytics over gathered data, and derive useful knowledge. Some efficient processes that can be used for the selection of adequate forecasting methods are described in [5].

For processing time series data, one of the most commonly used methods includes data classification. There are many examples of successful usage of data classification processes, some of which are used in adapting the mobility management mechanisms [6], prediction of applications' data consumption [7], and user activity [8].

In this paper, the several commonly used models for time series data analytics, described for instance in [9], and some additional models, described in more detail in [10], are taken into account. In [10], the analysis is conducted to point to the fact that the presented models enable an adequate forecast of the number of future service users.

However, the aim of the analysis conducted in this paper, unlike the one conducted in [10], is to demonstrate that the predictive modeling processes can also be used for selecting the best service offerings for chosen scenarios. This is particularly important for enhancing business planning processes and the selection of the most effective business models.

A. Common Models Used in Predictive Modeling

The scope of this paper covers the analyses of several common models [9], as well as additional predictive models [10], with the objective to compare their predictive accuracy.

1) Simple Logistic model

The simple Logistic model is a commonly used model for the forecasting of service market adoption, and is defined by the following expression:

$$L(t;M,a,b)=\frac{M}{1+e^{-a(t-b)}} \qquad (1)$$

where L represents the number of broadband users per capita over period t. The model is defined by the following parameters: M, which reflects the market capacity; a, which reflects the speed of broadband adoption; and b, which positions the graph on the timescale.

2) Richards model

Richards model is called the Logistic model of four parameters, and is defined by the following expression:

$$R(t;M,a,b,c)=\frac{M}{\left[1+e^{-a(t-b)}\right]^{c}} \qquad (2)$$

where R represents the number of broadband users per capita over period t. The model is defined by the following parameters: M, which reflects the market capacity; a, which reflects the speed of broadband adoption; b, which positions the graph on the timescale; and c, which positions the model's inflection point.

3) Bass model

The Bass model represents the most commonly used model for prediction of new services, and is defined by the expression:

$$B(t;M,p,q,t_s)=M\cdot\frac{1-e^{-(p+q)\cdot(t-t_s)}}{1+\dfrac{q}{p}\cdot e^{-(p+q)\cdot(t-t_s)}} \qquad (3)$$

where B represents the number of broadband users per capita over period t. The model is defined by the following parameters: M, which reflects the market capacity; p, which reflects the coefficient of innovation ($p > 0$); q, which reflects the coefficient of imitation ($q \geq 0$); and t, which reflects the time when the service was introduced in the market ($t \geq ts$).

4) Gompertz model

The Gompertz model is a special case of a Logistic function, and is defined by the following expression:

$$G(t;M,a,b)=M\cdot e^{-e^{-a(t-b)}} \qquad (4)$$

where G represents the number of broadband users per capita over period t. The model is defined by the following parameters: M, which reflects the market capacity; a, which reflects the speed of broadband adoption; and b, which positions the graph on the timescale.

B. Additional Predictive Models

In order to expand the analysis and compare features of additional models, combinations of some other parameters are taken into account and combined models are derived, as described in more detail in [10], using the following expression:

$$BB(t)=M\cdot\frac{e^{\left[1-e^{-a(t-b)}\right]^{d}}}{e^{\left[1+e^{-a(t-b)}\right]^{c}}} \qquad (5)$$

where BB(t) denotes the number of broadband users, and M a total capacity. These modified forms take into account several additional combinations of parameters' values, previously defined in [10], as presented in Table I.

TABLE I. OVERVIEW OF ADDITIONAL PREDICTIVE MODELS

Models:	**Parameters values:** Parameter c:	Parameter d:	Notes:
Logistic (L)	1	0	
Bass (B)	1	1	
Richards (R)	$c \in \left\|0,+\infty\right\rangle$	0	*For* c=1: R ≡ L
Gompertz (G)	0	1	Subcases of c for d=0 and d=1
	1	0	
GB	1	1	
GR	$c \in \left\|0,+\infty\right\rangle$	0	Subcases: (c=0, d=0) and (c=1, d=0)
GBR	$c \in \left\|0,+\infty\right\rangle$	1	Subcases: (c=0, d=1) and (c=1, d=1)

1) GB model

The GB model combines the features of the Gompertz (G) and Bass (B) models. Like the Gompertz model, it has a fixed inflection point and the three parameters, *M*, *a*, and *b*, respectively.

$$GB(t;M,p,q,t_s) = M \cdot \frac{e^{\left[1-e^{-(p+q)\cdot(t-t_s)}\right]}}{e^{\left[1+\frac{q}{p}\cdot e^{-(p+q)\cdot(t-t_s)}\right]}} \qquad (6)$$

It models the fast growth. Moreover, this model can also be expressed by the parameters *p* and *q*, comprised within the Bass model.

2) GR model

The GR model combines the features of the Gompertz (G) and Richards (R) models and models fast growth. Like the Richards model, it has a flexible inflection point and the four parameters, *M*, *a*, *b* and *c*, respectively.

$$GR(t;M,a,b,c) = M \cdot \frac{e}{e^{\left[1+e^{-a(t-b)}\right]^{c}}} \qquad (7)$$

3) GBR model

The GBR model combines the features of the Gompertz (G), Bass (B) and Richards (R) models. It has a flexible inflection point and the four parameters, *M*, *a*, *b* and *c*, respectively. It also models the fast growth.

$$GBR(t;M,a,b,c) = M \cdot \frac{e^{\left[1-e^{-a(t-b)}\right]}}{e^{\left[1+e^{-a(t-b)}\right]^{c}}} \qquad (8)$$

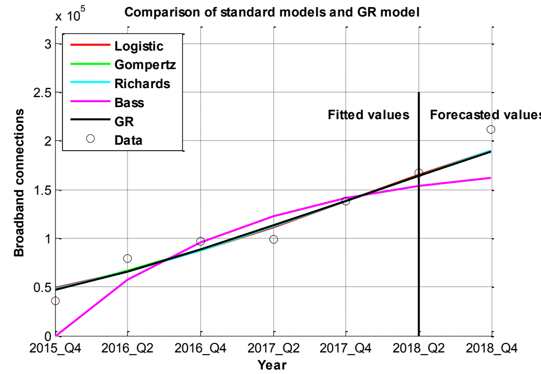
The predictive models can be additionally modified using more explanatory parameters. Although certain generalizations of the existing models expand their features' description, additional parameters require larger sets of known data points used in the predictive modeling process, which limits their usage.

IV. MODELING OF SERVICES ADOPTION PROCESS

All these models are suited for modeling of services adoption trends. For the given models, the analyses that point to the accuracy of fitting and forecasting processes are conducted. The estimated parameters can be used to generate the prediction of future values based on the known ones.

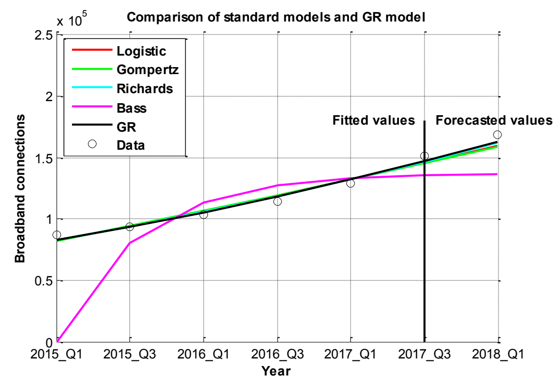
A. Fitting Process

As can be seen from the results presented in Figures 3-5, the fitting processes comprise the adjustments of models parameters to best describe the default time series values (denoted as '*Data*') representing the number of users and revenues, respectively. The results point to the fact that the Bass model can model faster growth, but its accuracy improves as the number of known data points, i.e., the ones used for training, increase. All other models show similarly good properties in the presented cases, despite somewhat scattered data set for quarterly periods presented in Figure 3.



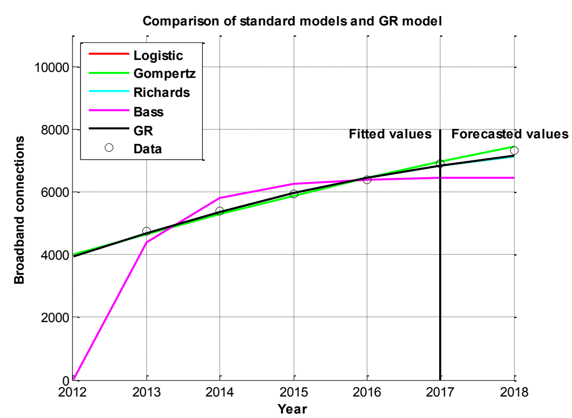
Time period:	2015_Q4	2016_Q2	2016_Q4	2017_Q2	2017_Q4	2018_Q2	2018_Q4
The nr. of users of the 4D service packages:	35.772	79.168	96.750	98.642	138.536	166.807	211.762

Figure 3. The number of users of the 4D services packages [1].



Time period:	2015_Q1	2015_Q3	2016_Q1	2016_Q3	2017_Q1	2017_Q3	2018_Q1
The nr. of users of the M2M/IoT services:	87.281	93.586	103.948	114.667	129.046	151.643	168.854

Figure 4. The number of users of the M2M/IoT services [1].



Time period:	2012	2013	2014	2015	2016	2017	2018
The global revenue of IoT (in mil. EUR):	3.900	4.750	5.400	5.950	6.400	6.900	7.350

Figure 5. The global revenue of IoT (in mil. EUR) [2].

B. Forecasting Process

A number of measures are used to determine the accuracy of forecasts [6]. Statistical criteria can be selected only after making the decision about the general type of forecasting method. There are mainly four types of forecast-error metrics: scale-dependent, percentage-error, relative-error, and scale-free error metrics. The chosen statistical metrics that describe the accuracy of forecasted time series values are the forecast error and the mean absolute deviation, as good metrics to use when analyzing the error for a single output, and considering the fact that the prediction errors are in the same unit as the original series. The Mean Absolute Deviation (MAD), also commonly called the Mean Absolute Error (MAE), is the measure of aggregate error defined by the expression:

$$MAD = \frac{\sum_{i=1}^{n} |E_i|}{n} \tag{9}$$

where n is the number of prediction errors which are used for the calculation, and forecast error, E, is the difference between the actual value and the forecasted value in the corresponding period t. A smaller value of the mean deviation denotes the model's better prediction performance.

The sample data set is divided into subsets which comprise the training data (shaded in Figures 3-5) - used for the model parameters fitting, and the testing data (all other) - used for determination of the accuracy of the forecasted values. The chosen available data sets comprise the number of users of the 4D services packages [1], the number of users of the M2M/IoT services [1], and the global revenue of IoT [2].

C. Overview and Analysis of Results

Considering the gathered results of the conducted fitting processes presented in Figures 3-5, and the conducted forecasting processes presented in Figures 6-8, the primary difference among the models' fitting and forecasting accuracy is caused by different positions of the models' inflection points.

As presented in Figures 3-8, the Bass model shows limitations both in fitting and in the forecasting of the initial short-term upper market capacity. All other models show good fitting properties, as presented in Figures 3-5. Moreover, the Logistic model is less accurate in the forecasting of accelerated growth, as presented in Figure 8, and is more suitable for modeling of slower growth. It can also be noticed that, in the slower growth phase, the simple Logistic model gives the most accurate forecasting results, as presented in Figure 7. Furthermore, the good forecasting properties of the Richards model within the growth phase are caused by its flexible inflection point, which can be accurately adapted to the given changes in the modeling values, as presented in Figures 6-8. Finally, the Gompertz model shows a good accuracy in forecasting within the growth phase since it adequately models the accelerated growth of values, as presented in Figures 6-8.

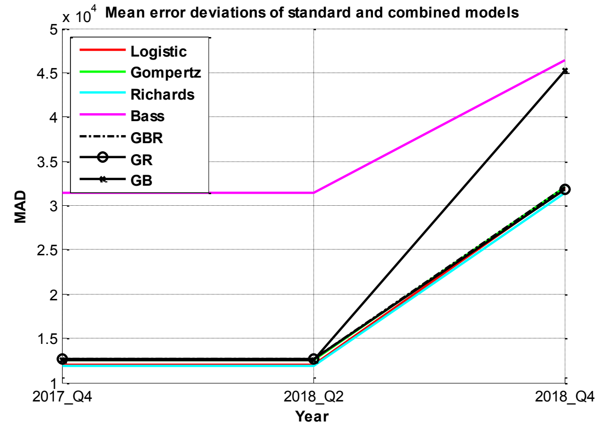


Figure 6. The number of users of the 4D services packages.

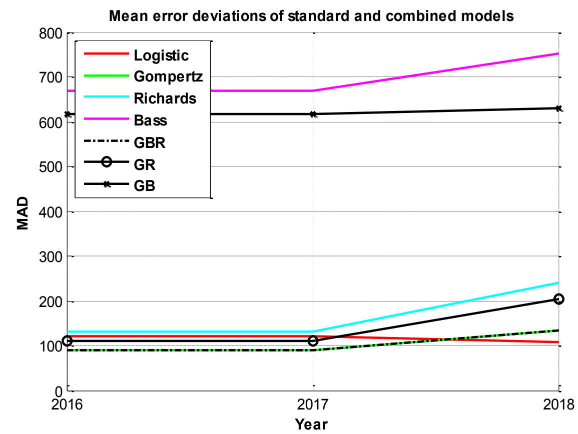


Figure 7. The global revenue of IoT (in mil. EUR).

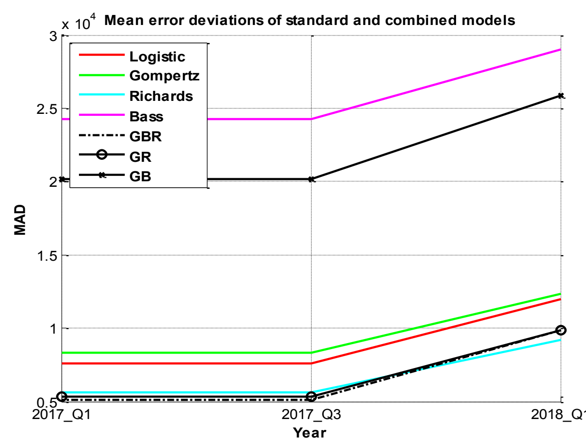


Figure 8. The number of users of the M2M/IoT services.

The additional GB, GR and GBR models combine the features of the Gompertz (G), Bass (B), and Richards (R) models. The combined models that have the features of the Gompertz model accurately predict the fast growth. However, the lack of the Gompertz model relates to the fact that it can not limit the excessive growth in the long run, and this can reflect the forecasting accuracy of the combined models, as well.

Since the Bass model has difficulties in assessing the exact upper market capacity limit in the initial growth phase, the forecasting accuracy of the Bass model combined solely with the Gompertz model, i.e., the GB model, is also not adequate, as presented in Figures 6-8.

However, the model that combines the features of the Bass model with the Gompertz and Richards models, i.e., GBR model, is more accurate for forecasting of the long-term adoption of the services since having a flexible inflection point which limits the accelerated growth in values, as presented in Figures 6-8.

The combined models that use the features of the Richards model, i.e., the GR and GBR models, generally show good forecasting properties even if the minimum number of values is used in fitting, as presented in Figures 3-5.

The Richards model accurately forecasts significant growth in the long run since it uses a flexible inflection point in order to adjust growth to the last existing training value, which can be seen for the GR and GBR models, as presented in Figures 6-8.

For a sum-up of the presented results, the models that combine the features of the Richards model with the Gompertz model achieve good fitting to fast growth and show good forecast results in all presented examples.

V. Conclusion

Since fast changes in the telecommunications markets around the world impact services development and adoption trends, users' demand for services features continuously changes. Advanced telecommunications services bring many advantages and added value to end users, so further growth in their adoption is inevitable. However, given the accelerated trends in services development, there is often not a lot of time to thoroughly consider users' requests related to services offerings before launching services in the markets. So, one of the challenges operators currently cope with is the way which makes it possible to select the best services offerings based on accurate forecasts of changes in market conditions and to estimate the adoption trends of novel telecommunications solutions. With regard to the presumption of usage patterns of novel services, it is possible to track usage patterns of similar services to create stronger business models.

In this paper, the analytics of telecommunications services adoption processes are conducted for the gathered smaller sets of time series data, i.e., for the short-term modeling period. For the chosen case study examples, the analyses of services adoption trends are compared based on the accuracy of forecasted model parameters. An overview and comparison of the accuracy of the predictive modeling of broadband services adoption using common adoption growth models are given. Alongside standard models, additional combined models are used to present their predictive capabilities, and to compensate for some lacks of the commonly used adoption models (for instance, of a Bass model which is not suitable for modeling of services adoption in the initial services' introduction on the market). The presented results point to fast expected growth in the number of services users.

Moreover, the presented results could be used to define adequate M2M/IoT services offerings. Based on the given results, the conclusion that can be taken as a guideline for the business modeling process is the fact that, despite their expected growth, and due to general risks related to slower demand for novel services, the M2M/IoT services can be offered within the packages combined with other types of services that already have their strong user base, which was presented as a good solution, considering the fast adoption growth of the package services.

Business models can be modified accordingly to enhance broadband adoption, boost revenue, or limit user churn rates in order to improve overall market dynamics.

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 ISBN: 978-1-61208-727-6