Distribution and Allocation of Network Resources Based on Predictive Analyses of Time-Series Telecommunications Data

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Abstract *– With the fast development of different communication technologies, applications, and services, the adoption of advanced sensory and computing solutions, such as the various Internet of Things (IoT) and mobile computing solutions, is continuously growing. The massive adoption of mobile computing and IoT sensory devices encouraged the continuous growth of generated network traffic. Therefore, the selection of adequate solutions for efficient data processing became necessary. Despite numerous advantages arising from effective data processing, operators and enterprises working within the ICT domain have only limited amounts of available networking resources to store, process, and use valuable information extracted from large quantities of gathered data. In this paper, an optimal planning process and prediction of usage of network resources is examined. It takes into consideration the results of predictive modeling processes based on available sets of time series telecommunications data. The given forecasts enable effective selection of network architectures, as well as the distribution and allocation of network resources considering the cloud, edge, and fog networking concepts.*

Keywords*: optimal network resources allocation; edge-fog-cloud management for networking load distribution; telecommunications time-series data analyses; predictive analyses*

1. INTRODUCTION

The significant advances in the development of information and communication technologies (ICT) have led to the massive adoption of various mobile computing and sensory devices, as well as an exponential growth of generated wireless network traffic [1]-[6]. A constant evolution and adoption of advanced technological solutions, such as the Internet of Things (IoT) solutions, expands opportunities for implementation of the Internet of Everything (IoE) ecosystems. These intelligent ecosystems are comprised of a large number of distributed heterogeneous devices that consistently generate vast amounts of data.

According to some estimates, within a few years, there will be several hundred billion connected IoT devices affecting every aspect of life, ranging from personal, public or industrial smart environments [1]. In this context, sensors have a crucial role in enabling the collection of various types of acquired data [7]. For handling massive amounts of data originating from numerous sources, increasing attention is given to the efficient transfer of network traffic and data processing techniques [1]. Overall growth in the volume of network traffic and the development of the next generation ICT ecosystems encourage telecom operators and enterprises in the ICT domain to adapt their existing networking approaches, [4] and [6]. Adjusting network settings can achieve efficient distribution and allocation of resources for caching, processing, and computing. Due to existing requirements related to the performance of novel ICT systems, optimal selection of adequate network architectures became a very challenging task. The processes of appropriate network resource distribution and allocation significantly impact data processing speed. Therefore, these processes can be additionally supported by the implementation of algorithms for adaptive resource management, taking into consideration data usage patterns, as well as adequate techniques for traffic offloading [1]. The processes of prediction-based planning, distribution, and allocation of network resources present significant challenges. The selection of adequate predictive models can effectively contribute to the optimization of planning processes, as can also be seen based on the results of analyses presented in this paper. Telecommunications data analytics usually takes into consideration time-series data reflecting adoption or deployment rates of particular ICT solutions. The gathered results point to specific requirements that are necessary for optimization. If data representing ICT solutions' adoption and deployment patterns are taken into consideration to derive useful knowledge, suitable prediction models must be used. This aspect is particularly important because a vast number of telecom operators and enterprises in the ICT domain search for the best solutions for the distribution and allocation of their limited caching and computing resources.

In this paper, the analytics of gathered available telecommunications data sets are conducted based on the results created using several predictive models. The smaller sets of time series data are taken into consideration. In Section 2, an overview of current trends in adoption and deployment of relevant telecommunications solutions is presented, as a starting point for further prediction-based forecasts and planning processes. In Section 3, the differences between centralized and decentralized network architectures, and between edge and fog computing concepts are presented. In Section 4, an overview of several common and some additional predictive models are presented, and the usage of gathered results in processes of network resources allocation and distribution is accentuated. In Section 5, the defined models are applied to collected data sets, and the obtained results are carefully analyzed. The optimal approaches in making decisions related to network resources distribution and allocation are indicated based on predictive analyses results, and the most important conclusions are highlighted.

2. ADOPTION TRENDS OF TELECOMMUNICATIONS SOLUTIONS

The telecom operators and enterprises working within the ICT domain have high expectations for scale and scope arising from advanced ICT solutions offerings [1]. The additional information extracted from a large amount of collected network traffic presents added value that encourages a significant incentive for advanced ICT services development and implementation processes. These expectations induce new research challenges related to available network settings. Higher levels of availability and quality of ICT solutions induce additional growth of their adoption, which is closely correlated with total achieved gains. The majority of businesses based upon usage of advanced ICT solutions monitor metrics that reflect improvements in the efficiency of these solutions [5]. Therefore, the analyses and comparisons of models involving different ICT solutions are prerequisites for the business planning processes since a timely application of relevant data represents an essential advantage within business modeling process. For a better overview of current trends in the adoption of ICT solutions, various data sets reflecting their adoption rates can be used [2]-[5]. Some conclusions that can be defined based on the analysis of these data are presented hereafter.

A) The generated network traffic and the number of Internet connections

An increase in the number of Internet connections is generally followed by a growth in total generated network traffic [4]. The main reason behind the existing massive network traffic growth is in the usage of audio and video-on-demand content, whose quality continuously increases [1]. Furthermore, the users' expectations related to the quality of services continue to rise. Uninterrupted high-speed connectivity is becoming an essential requirement for most users, regardless of their location or the chosen network access solutions. An increase in average traffic consumption per user is mostly caused by the rise in the adoption of bandwidth-intensive video services streaming. Besides the audio-visual media which accounts for the majority of network data traffic, the exchange of data traffic among end-user devices, terminal network equipment, servers and storage in the cloud continues to grow significantly, as well. Increase in types of available solutions users can choose to connect to the Internet, i.e., increase in the availability of Internet access technologies and services, follows growth in overall Internet network traffic demands. Intensive adoption processes of a wide range of Internet access solutions are currently available, as well [4]. The significant advances in the development of wireless ICT solutions have led to the massive adoption of mobile broadband connections [4]. Moreover, the growth of the mobile subscriber base is expected to continue within the next few years, with mobile broadband constituting a majority of the personal mobile subscriptions. Machine–to–Machine (M2M) connectivity also has the potential of becoming one of the contributors to the expected growth. The M2M services, as a part of the IoT solutions, which include automated communication and data transmission among two or more ICT entities, also record growth in demand [4]. Although common characteristics of IoT and M2M reside on remote access to devices, IoT is expanding the concept of M2M since it can be integrated into comprehensive and flexible business solutions. While IoT is focused more on software solutions and the Internet Protocol (IP) based networking, M2M communication is predominantly oriented on embedded hardware and mobile networks. However, considering the fact that M2M with Internet Protocol represents a part of IoT, the M2M/IoT services adoption trends can be analyzed jointly.

B) The generated network traffic and the package services

Considering the fact that every market has its limited maximal capacity, i.e., the total number of end-users, an additional increase in ICT market share can be achieved with growth in the number of adopted services. As already proven in many cases, services diversification represents a key driver of revenue growth for service providers, e.g., telecom operators or ICT enterprises, since end-to-end solutions enable the most significant differentiation. While some operators specialize in specific ICT segments, others focus on specific vertical markets. However, many operators tend to invest in new areas of growth. Therefore, the key to sustainable growth is in expanding beyond the core ICT services offerings. A possible solution for the increase in the number of services offerings can be achieved with the IoT services offerings. The IoT can induce positive growth because each offer can include a different combination of connectivity, devices, applications, and services. Many different types of ICT services offerings are currently available in the markets [5]. Although the stand-alone service offerings have a strong base of users, offerings of services packages comprising of more than one ICT service have also achieved fast adoption rates. These are any service packages where two or more ICT services are provided to users jointly, e.g., Internet, telephone services in the fixed network, telephone services in the mobile network or/and TV services. These are packages that jointly offer two or more services (e.g., 2D, 3D, and 4D packages). The 4D packages, which include Internet access, TV, and the fixed and mobile telephone services, note for fast adoption growth, mainly based on their total value [4]. This fact 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 [7].

C) The generated network traffic and the number of installed base stations

The seamless connectivity is one of the main contributors inducing growth in the adoption of wireless solutions, along with increasing bandwidth demands. The exponential growth of wireless network connectivity necessitates the convergence of dense heterogeneous networks since a single base station may not be able always to provide the high quality of services necessary for services demanding high data rates, as in a case of multimedia streaming.

Legacy mobile networks are dominated by macro cells served by high-powered cellular base stations whose radio coverage range of a few kilometers to tens of kilometers. As a response to the massive growth in network traffic, mobile operators have options to additionally upgrade their networks and provide even higher network capacities and user throughputs. One of the possible solutions for improvement is to maintain multi-standard radio access networks which provide capacity scalability due to increased spectral efficiency in existing bands. Also, improvements can be based on the usage of adequate modulation and multi-antenna techniques, and aggregation of a large number of licensed and unlicensed carrier bands. Furthermore, network densification also improves network capacity. It assumes changes in network topology or architecture by adding new cell sites. An appropriate network architecture should be chosen in combination with diverse factors. An increase in the number of radio sites using small cell sizes is an essential element for capacity increase. Small cells, as low-powered radio access nodes, are used to increase capacity without a need for tower-based radio sites. They operate in the licensed or unlicensed spectrum and typically cover areas range from ten meters to several hundred meters. Various types of small cells co-exist. These variants include femtocells, picocells, microcells, and metro cells. Network densification process achieved by adding small radio sites improves network coverage and capacity, enhances spectrum efficiency, and lowers energy power requirements. The usage of small cells operating on unlicensed bands is adequate in scenarios in which the deployment of network infrastructure is not commercially attractive for network operators, leaving that areas insufficiently covered by network services (e.g., as in some rural scenarios), as well as in scenarios with a scarce or limited volume of available network resources, as for instance, for a limited required radio frequency spectrum and a high network traffic demands (e.g. as in some urban scenarios). The small-cell based network access provides adequate coverage options for areas lacking basic network infrastructure (e.g., Fi-Wi or LPWA), as well as for offloading of network traffic on license-exempt frequencies (e.g., using Wi-Fi or LoRa) to free up the capacity in the macro network layer.

3. OVERVIEW OF COMPUTING NETWORK ARCHITECTURES

The geographic distribution represents the scale to which a system is widely spread or localized. Within this context, a type of network architecture that should be used in the given scenario, i.e., the centralized or decentralized architecture, depends mainly on the utility of implemented ICT system, and the intended usage of information extracted from the processing of collected data traffic. The available computing network architectures are the Cloud Computing (CC), Edge Computing (EC), Mobile Cloud Computing (MCC), Mobile Edge Computing (MEC), and Fog Computing (FC), as presented in Table I [8].

Table 1. Computing network architectures.

Network architecture	CC	EC	MCC	MEC	FC
Users	Any	Any	Mobile	Mobile	Any
Providers	Service providers	Enterprises / Network providers	Users / Service providers	Network providers	Users / Service providers
Initiative	Academic / Industrial	Academic / Industrial	Academic	Academic / Industrial	Academic / Industrial
Network architecture	Centralized / Hierarchical	Distributed / Localized	Central cloud & Distributed mob. devices	Localized / Hierarchical	Decentralized / Hierarchical
Internet connectivity	Necessary while running services	Not necessary, can operate autonomously	Necessary for offloading and obtaining content from the cloud	Not necessary, it can operate autonomously or connect to Int. using RAN	Not necessary, can operate autonomously
Hardware connectivity	WAN	WAN, (W)LAN, WiFi, cellular, ZigBee	WAN	WAN, cellular	WAN, (W)LAN, WiFi, cellular
Service access	Through the core network	At the edge	Through the core network	At the edge	Through devices from the edge to the core network

A) The Cloud Computing (CC)

A Cloud Computing (CC) model provides on-demand access to shared network computing resources [9]. Depending on the part of the application stack that can be managed by cloud users for processing, storage, and networking, the cloud offers the following models: infrastructure, platform, and software as services models (IaaS, PaaS, and SaaS) [10]. Because the demand for cloud resources can change within time, computing based on the provisioning of the required resources includes the virtualization for the deployment of on-demand applications. With the increase in the number of connected networking devices, services and applications, cloud architectures enable easy and cost-effective processes of computing, data caching and connectivity, but access to centralized resources can cause delays and degraded performance for devices that are located far from centralized cloud or data center sources.

B) The Edge Computing (EC)

Edge Computing (EC) architecture enables placing servers, applications, or small clouds at the edge of the network. The term 'edge' used by the telecom operators usually refers to 4G and 5G base stations (BSs), Radio Access Networks (RANs), and Internet Service Providers' (ISP) access and edge networks. Moreover, that term is recently used also in the IoT context, as pointed in [11], and [12]. It refers to the local network in which sensors and IoT devices are placed. Therefore, the edge presents the first hop from the IoT devices, such as gateways or access points, but not the IoT nodes themselves. The usage of edge computing is intended to enable storage and compute resources closer to the user [13]. EC connects the IoT devices with the cloud. It enables data filtering, preprocessing, and aggregating using cloud services implemented near IoT devices [11].

- The Edge Computing (EC) vs. Cloud Computing (CC):

When placed at the network edge, storage, and compute systems reside closer to device, application, or user that produces the data to remove data processing latency. In this way, it is not necessary to send data from the edge of the network to some remote cloud or any centralized processing system, and back. By reducing the distance and time necessary to send data to the centralized system, the speed of data transfer, as well as the performance of services and applications on edge can be improved. The EC is adequate for industrial IoT usage cases since it brings processing closer to the sensors and actuators, and enables edge analytics of local data.

C) The Mobile Cloud Computing (MCC)

Mobile Cloud Computing (MCC), presents infrastructure outside of the mobile device where the data storage and processing are conducted [14]. MCC shifts most of the computation from mobile devices to the cloud, and therefore increases the mobile devices' battery life. However, offloading computation tasks to the cloud causes a relatively high latency for the delay-sensitive applications. MCC enables coordination between IoT devices, mobile devices, and cloud computing. This allows the running of data-intensive and computing-intensive IoT applications [15].

- The Mobile Cloud Computing (MCC) vs. Cloud Computing (CC):

MCC shares the characteristics of Mobile Computing (MC) and CC. As opposed to mobile computing which is resource-constrained, in MCC, the high availability of computing resources is present. In MCC, the availability of cloud services is higher than that of mobile computing.

- The Mobile Cloud Computing (MCC) vs. Edge Computing (EC):

Unlike MCC, EC is located at the edge of the network. Due to proximity to the IoT devices and users, latency in EC is in general lower than in MCC and CC. In the EC, connected devices are not limited by the resources as in standard mobile computing. EC uses small data centers and has higher service availability since devices do not have to wait for a centralized service.

D) The Mobile Edge Computing (MEC)

Within Multi-access Edge Computing, i.e., Mobile Edge Computing (MEC) system, functional, management, and orchestration entities, enable applications to run as virtual machines in a virtualized computing environment [16]. MEC elements are co-located with base stations. They deploy virtual machines for performing virtualization of routers and firewalls' functions to improve network efficiency, and cache content services to enhance user experience. Since edge architecture supports a specific access network, either wireless or wireline, the MEC infrastructure is deployed and owned by the telecom operators.

- The Mobile Edge Computing (MEC) vs. Cloud Computing (CC):

MEC is an extension of MC through EC. MEC presents a platform providing CC features within the Radio Access Network (RAN) close to mobile users.

- The Mobile Edge Computing (MEC) vs. Edge Computing (EC):

MEC extends EC by enabling computing and storage near mobile devices. MEC enables adding of EC functionality to the existing RAN base stations. In MEC, small data centers with virtualization can be used. In MEC and EC, computing resources are lower than in CC due to the available hardware. MEC supports low-latency applications. Both EC and MEC can operate even without Internet access. While MEC enables connections through a WAN, cellular, or WiFi, EC enables connections using LAN, cellular, or WiFi. MEC enables EC to various mobile devices [17], as well as the usage of applications sensitive to delays over the mobile network [18]. MEC has also incorporated the Software-Defined Networking (SDN), as well as Network Function Virtualization (NFV) capabilities. SDN enables easy management of virtual networking devices through software Application Programming Interfaces (APIs), and NFV enables faster deployment of networking services through virtualized infrastructure [19]. Using SDN and NFV, the orchestrator can be used to coordinate the resource provisioning across multiple network layers [20].

- The Mobile Edge Computing (MEC) vs. Mobile Cloud Computing (MCC):

Increased adoption of wireless solutions induces further growth in mobile data traffic. The generated large quantities of multimedia traffic need to be processed by keeping up to demands set on users' experience. To overcome the existing data processing limitations of radio access networks, the following complementary approaches are proposed: one which suggests the centralization of base station functions using virtualization and shifting of computing capabilities to the central cloud, i.e., the Cloud Radio Access Network (C-RAN), and the other which suggests shifting of computing capabilities to the edge, i.e., the Mobile Edge Computing (MEC). Unlike MCC, related to the cloud service users of mobile devices and cloud service providers, MEC focuses on RAN-based infrastructure [18].

E) The Fog Computing (FC)

In Fog Computation (FC), storage, computing, and data management occur in the cloud but also along the path on which data travel to the cloud. FC presents a horizontal architecture platform that enables computing, storage, control, and networking functions closer to the users [21], and allows the distribution of computing functions between different platforms [22]. In FC devices either serve as computing nodes or use fog resources. FC is mainly implemented in devices (e.g., small servers, gateways, access points, routers, or switches) owned by ICT enterprises.

- The Fog Computing (FC) vs. Cloud Computing (CC):

While CC must be accessed using the core network, FC can be accessed using connected devices from the edge to the network core. While CC provides computing resources using high power consumption, FC provides computing resources at lower power consumption [23]. CC devices need Internet connections for cloud services. The FC can work independently and send necessary updates to the cloud when an Internet connection is available.

- The Fog Computing (FC) vs. Edge Computing (EC):

FC extends EC capabilities given computation distribution and traffic load balancing. While EC orchestration and management derive from specific vertical practices of legacy systems, such as mobile network, FC provides an architecture which incorporates tools for distributing, orchestrating, and managing resources and services across networks. FC orchestration enables the pooling of resources and collaborations between fog nodes which helps load balancing. FC and EC both move the computation and storage to the network edge. However, while FC provides computing, networking, and storage in any place from cloud to devices, EC provides computing at the edge [21]. EC is optimized for a single type of network resources. FC supports cooperating nodes running distributed applications, and heterogeneous environments on any node. FC's architecture permits every fog node to be equipped with the necessary dynamically configured resources and provides a balance of computation and storage capabilities. While FC focuses on interactions between edge devices, EC focuses on the technology of connected devices [12].

- The Fog Computing (FC) vs. Mobile Cloud Computing (MCC):

FC can be integrated within the radio access networks (RAN), and form the so-called Fog RAN (F-RAN). F-RAN may be used for data caching at the edge [24]. Cloud RAN (C-RAN) virtualizes the base station functions [25] and provides centralized control over F-RAN nodes. Both F-RAN and C-RAN are appropriate for cellular networks with base stations.

- The Fog Computing (FC) vs. Mobile Edge Computing (MEC):

The MEC computing process aligns with the emerging concept of FC. However, these somewhat differ. While MEC extends computing capabilities to the edge of the radio access network with a new interface between the base stations and upper layers, FC architecture brings the processing and storage resources to the lower layers for occasionally connected mobile ad-hoc and sensory devices.

The majority of the research conducted in the field of edge and fog computing is related to schemes that deal with the topics related with improvement of the Quality of Service (QoS) by minimizing latency or data losses, the topics related with the scalability by efficiently scaling to the large magnitude of IoT networks, and the topics related with the heterogeneity of devices, as presented for instance in [26], and [27]. Also, the network management schemes are in the research focus, as presented, for instance, in [28] and [29]. The problems related to management of latency-sensitive IoT applications is evident in [30]. Moreover, it is important to mention that the cloud applications can fully or partially migrate to edge [31]-[32], and inversely [33]-[34] however the streaming a massive amount of data to the cloud imposes considerable energy consumption.

4. PREDICTIVE MODELS

An overall increase in generated network traffic and a limited amount of available network resources have encouraged telecom operators and enterprises working within ICT domain to search for the optimal network architectures to enable the best approaches for storing and management of generated data traffic, applying analytics over gathered data, and deriving useful knowledge. Within this context, forecasting of ICT solutions' adoption rates can be used within planning processes to achieve efficient distribution and allocation of available network resources. The forecasting of adoption rates of various ICT solutions is increasingly important in optimal resources management.

Different predictive models whose implementation can impact planning processes are used [35]. The processes used for the selection of the forecasting methods are described in [36]. In processing time-series data, one of the most commonly used methods includes data classification. There are many examples of usage of data classification processes, some of which are applied, for instance, in adapting the mobility management mechanisms [37], prediction of applications' data consumption [38], and user activity [39].

In this paper, several commonly used models for time series data analytics, described for instance in [40] and [41], and some additional models, described in more detail in [42], are taken into consideration. In [42], the analyses are conducted to point to the fact that the presented models enable adequate forecast of the number of future service users, and in [41], to point to the fact that these models allow adequate forecast for finding the best service offerings. However, the aim of the analyses conducted in this paper, unlike the ones conducted in [41] and [42], is to point to the fact that predictive modeling processes can be used for selecting optimal network architectures for storing and processing of exponentially increasing generated network traffic, as well. This is particularly important for enhancing data processing speed and achieving higher levels of quality of services.

A) Common Models Used in Predictive Modeling

The scope of this paper covers the prediction-based analyses of ICT solutions adoption, used as the starting point to further processes of network resources distribution and allocation planning. The several standard, i.e., commonly used [40], as well as some additional predictive models [38] are used, to show and compare their predictive accuracy. The common models for the forecasting of adoption, and their related expressions for the Simple Logistic model, Richards model, Bass model, and Gompertz model, respectivelly, are:

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

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

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

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

where L, R, B, and G represent the volume of adopted solutions over period t, determined using the Logistic, Richards, Bass, and Gompertz models, respectively. The following parameters define these models: M, which reflects the market capacity; a, which indicates the speed of adoption; b, which positions the graph on the timescale; and c, which places the model's inflection point; p, which reflects the coefficient of innovation ($p>0$); q, which demonstrates the coefficient of imitation ($q \geq 0$); and t, which reflects the time when the solution was introduced in the market ($t \geq ts$).

B) Additional Predictive Models

To expand the analysis and compare features of additional models, combinations of some other parameters are taken into consideration, and combined models are derived, as described in more detail in [38], using the following expression:

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

where $BB(t)$ denotes the volume of adopted solutions, and M a total capacity.

Table 2. 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)

These modified forms take into consideration several additional combinations of parameters' values, previously defined in [38], as presented in Table III.

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

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

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

These models combine the features of the Gompertz (G), Bass (B) and Richards (R) models. They model the fast growth and are determined by the same parameters, M, a, b, c, p, and q, as common models. 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.

5. MODELING OF ICT SOLUTIONS ADOPTION

The given models (1)-(8) are used in forecasting adoption trends of several ICT solutions. The analyses of the accuracy of fitting and forecasting processes are conducted, and the parameters estimated within the fitting processes are used to generate the forecasts of future values, based on the known ones. The chosen data sets comprise data reflecting the total mobile and fixed network data traffic [2]-[4], total wireless data transmission capacity across all frequency bands [3]-[4], total number of GSM, UMTS and LTE base stations [3]-[4], number of users of stand-alone Internet services [5], number of users of 4D service packages [4]-[5], and number of users of the M2M/IoT services [4]-[5].

A) Fitting Process

As can be seen from the Figures 1-6, the fitting processes comprise the adjustments of models' parameters to best describe the real time series values (denoted as 'Data' [2]-[5]), representing the trends in adoption of several chosen ICT indicators. The fitting process is conducted within the time period from 2011 to 2020 in order to point to the fact that the smaller set of known data values is sufficient for forecasting of further values. The presented results point to the fact that the accuracy of the Bass model improves if the number of known data points, i.e., the ones used for training, starts with lower values. All other common models and GR model show good fitting properties in the given cases.

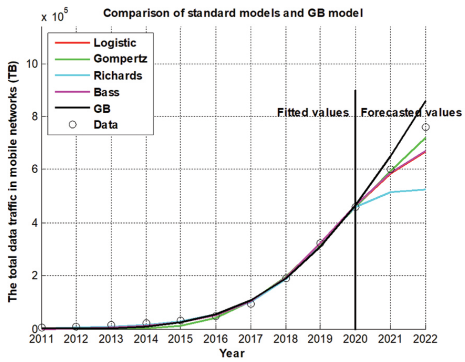


Fig. 1. The total data traffic in mobile networks (TB) [2]-[5]

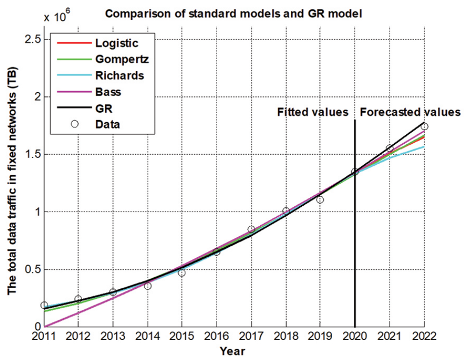


Fig. 2. The total data traffic in fixed networks (TB) [2]-[5]

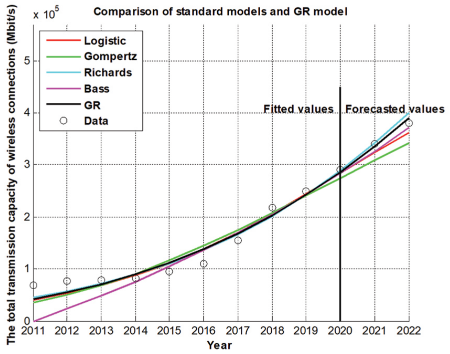


Fig. 3. The total transmission capacity of connections across all frequency bands (Mbit/s) [3]-[4]

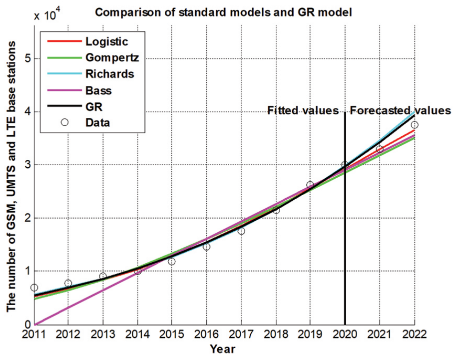


Fig. 4. The number of GSM, UMTS, LTE base stations [4]

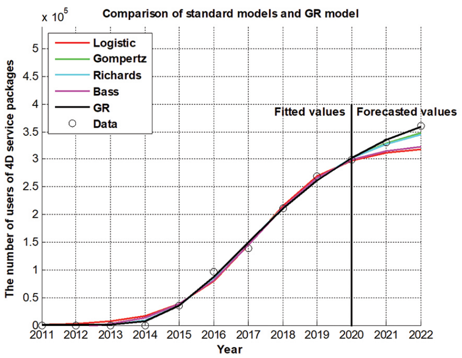


Fig. 5. The number of users of 4D service packages [3]-[5]

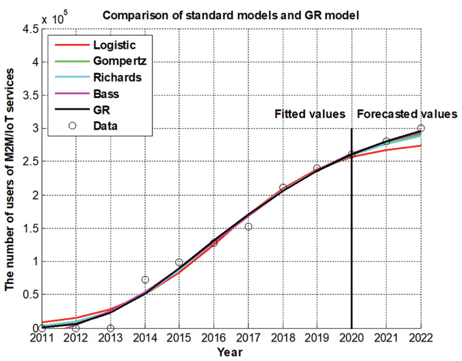


Fig. 6. The number of users of the M2M/IoT services [3]-[5]

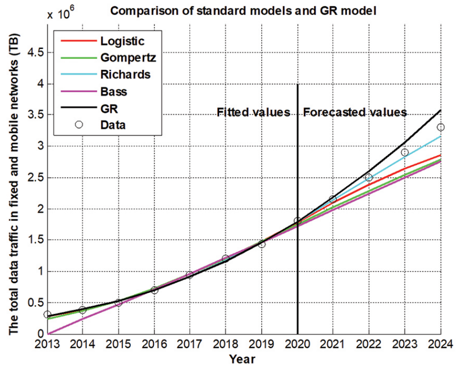


Fig. 7. The total data traffic in fixed and mobile networks (TB) [2]-[5]

Moreover, these models show very good fitting properties used for the longer forecasting time periods, as well, as presented by the values shown in Figure 7.

In Figure 7, the real data for the period 2014-2020 [4]-[5], and assumed data values of further growth in the period 2021-2024 are used according to the existing total network traffic growth trend.

B) Forecasting Process

Several measures are used to determine the accuracy of conducted forecasts. Statistical criteria can be selected after deciding on the general type of forecasting method [36]. There are mainly four types of forecast-error metrics: scale-dependent, percentage-error, relative-error, and scale-free error metrics. The chosen statistical parameters that describe the accuracy of forecasted time series values are the forecast error and the mean absolute deviation. These are adequate metrics in 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, is the measure of aggregate error defined by the expression:

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

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

The sample data set used for modeling is divided into subsets which comprise the training data (the shaded ones in tables below Figures 8-14) - used for the model parameters fitting, and the testing data (all other) - used for determination of the accuracy of the forecasted values. To determine the accuracy of the forecasted values, not only training data, but also testing data must be known, so data from the reports [2]-[5] are used.

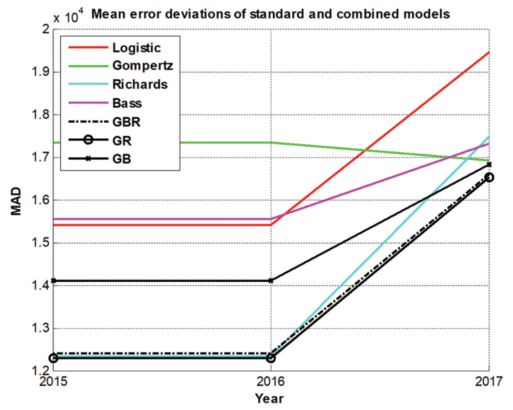
Considering the gathered results of the conducted fitting processes presented in Figures 1-7, and the undertaken forecasting processes shown in Figures 8-14, it can be concluded that the primary difference among the models' fitting and forecasting accuracy is caused by different positions of the models' inflection points.

As presented in Figures 1-14, the Bass model shows limitations both in fitting and in the forecasting of the initial short-term upper market capacity. All other models show very good fitting properties, as presented in Figures 1-7. Moreover, the common models show adequate accuracy in forecasting, as well, as presented in Figures 8-14.

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 cannot limit the excessive increase in the long run, and this can reflect the forecasting accuracy of the combined models, as well. Moreover, 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 always adequate, as presented in Figures 8-14. 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 8-14. The combined models that use the features of the Richards model, i.e., the GR and GBR models, generally show very good forecasting properties even if the minimum number of values is used in fitting, as presented in Figures 8-14. The Richards model accurately forecasts significant growth in the long run since it uses a flexible inflection point to adjust growth to the last existing training value, which can be seen for the GR and GBR models, as presented in Figures 1-14.

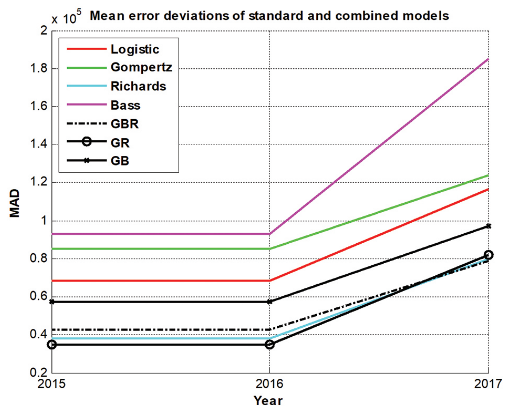
For a sum-up of the presented results, the models that combine the features of the Richards model with the Gompertz model achieve proper fitting to fast growth and show very good forecast results in all presented cases.

The purpose of the conducted analyses is to point to the fact that the predictive models can be used to adequately forecast values in many different usage cases, for instance, in the case of expected further growth in the total (fixed and mobile) network data traffic, as presented in Figure 7, as well as ICT indicators associated with it - growth in the network bandwidth usage, increase in the number of base stations, changes in the number of users of stand-alone services, as well as the growth in the number of users of package services and the M2M/IoT services. Moreover, additional significance and usefulness of these given forecasts are presented hereafter.



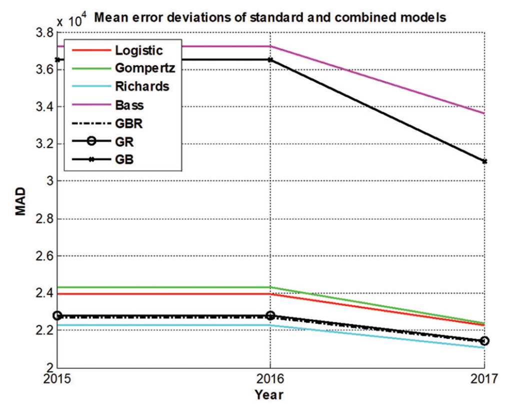
Period:	2011	2012	2013	2014	2015	2016	2017
The total data traffic in mobile networks:	3.552	8.329	15.712	22.270	32.408	49.173	92.033

Fig. 8. The total data traffic in mobile networks (TB) [2]-[4]



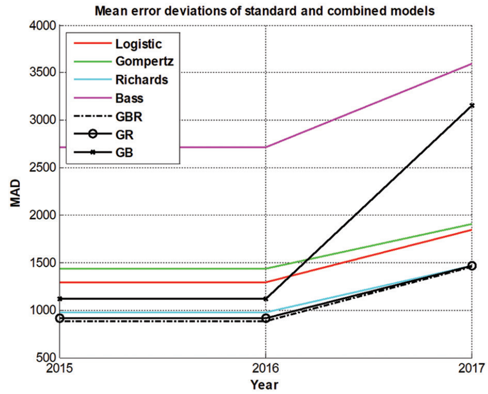
Period:	2011	2012	2013	2014	2015	2016	2017
The total data traffic in fixed networks:	188.821	238.408	299.890	362.482	480.880	660.547	846.846

Fig. 9. The total data traffic in fixed networks (TB) [2]-[4]



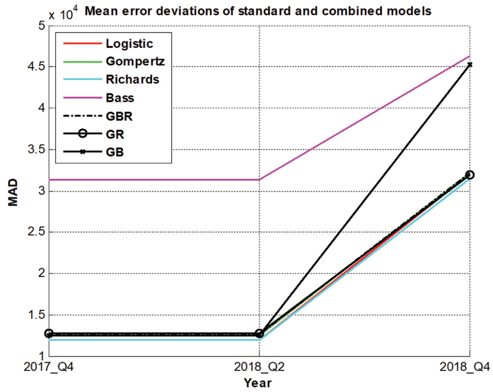
Period:	2011	2012	2013	2014	2015	2016	2017
Internet bandwidth usage (Gbit/s):	69.000	77.000	79.000	82.000	95.000	110.000	155.000

Fig. 10. The total transmission capacity of connections across all frequency bands (Mbit/s) [3]-[4]



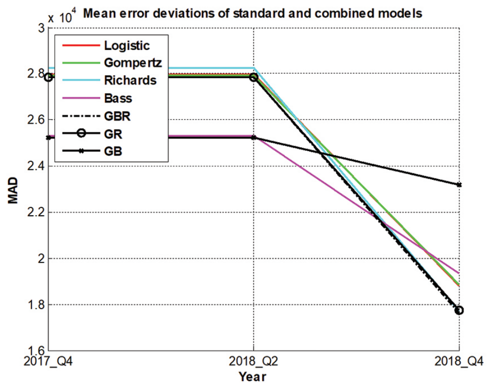
Period:	2011	2012	2013	2014	2015	2016	2017
The total number of GSM, UMTS, and LTE base stations:	7.031	7.709	9.026	9.985	11.914	14.711	17.566

Fig. 11. The number of GSM, UMTS, and LTE base stations [3]



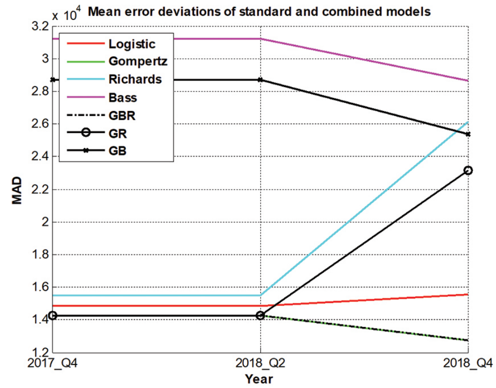
Period:	2015_Q4	2016_Q2	2016_Q4	2017_Q2	2017_Q4	2018_Q2	2018_Q4
The number of users of 4D packages:	35.772	79.168	96.750	98.642	138.536	166.807	211.762

Fig. 12. The number of users of 4D service packages [3]-[5]



Period:	2015_Q4	2016_Q2	2016_Q4	2017_Q2	2017_Q4	2018_Q2	2018_Q4
The number of users of stand-alone Internet services:	178.046	130.932	139.599	191.709	165.415	186.628	136.454

Fig. 13. The number of users of stand-alone Internet services [5]



Period:	2015_Q4	2016_Q2	2016_Q4	2017_Q2	2017_Q4	2018_Q2	2018_Q4
The number of users of M2M/IoT services:	98.375	108.138	127.446	147.716	152.654	172.142	211.677

Fig. 14. The number of users of the M2M/IoT services [4]-[5]

C) Analysis of results

Advanced telecom networks implement features that allow simultaneous management of network traffic originating from various types of terminal devices, services, and applications, having different requirements on the speed of data processing. The following analysis is conducted to point to the fact that the methods used in the selection of adequate network architectures for optimal distribution and allocation of available network resources and efficient data processing should be based on the forecasts of additional network traffic growth given by the best forecasting methods. According to the forecasted trends in growth of the network traffic presented in Figure 7, the forecasts of growth in adoption of related ICT solutions can be assumed as well, which are also assumed in reports [1], [4] and [6]. The processes of distribution and allocation of network resources used for data caching and computing based on predictive analysis results are placed in the scope of conducted research. The following analysis considers applying forecasted trends in adoption rates of ICT solutions as a starting point in the planning of distribution and allocation of network resources, as well as in the selection of adequate network architectures. The following guidelines can be defined based on the previously presented results, and reports [1]-[6].

- The results of the conducted analyses presented in Figure 1, Figure 2 and Figure 7 and reports [1], [4] and [6] forecast further growth in mobile and fixed network traffic.

The increase in data traffic is directly related to the development of the digital society. A significant increase in network data traffic is visible in both fixed and mobile networks, especially in the fixed network [4]. Moreover, within the last four years, the increase in data traffic has also been recorded among broadband users accessing Internet via wireless technologies in a fixed network [4]. Considering the importance of broadband internet access, as well as expected further investments in fiber access networks and 5G technology [4], support for significant additional growth of data traffic is expected in the following years.

Development in fixed communication networks is going in the direction of high availability of ultra-fast fiber optic networks, and in mobile networks in the direction of the introduction of the new 5G technologies [4]. The increasing convergence of these networks in the future will not only lead to even greater availability and the quality of existing services than to the emergence of new services and business models [6].

European policy makers have set broadband connectivity targets for Europe, and both wired, notably fiber, and wireless technologies play important role in delivering the target. The directives of the European Parliament and Council 2014/61/EU, refer to fixed (wired) and wireless to lower the costs for deploying broadband, while several national broadband development plans explicitly acknowledge the role of FWA, as a combination of different fixed and wireless technologies [6].

Table 3. Features of computing network architectures

Forecasts:	Demands:	Necessary features:	CC	EC	MCC	MEC	FC
Increase in generated network traffic	Content offloading using complementary network solutions	Heterogeneity support	✓	✓	✓	×	✓
	Content offloading using additional servers	Distributed storage support	×	✓	×	✓	✓
	Computation offloading	Virtualization support	✓	✓	×	✓	✓
Increase in bandwidth usage for wireless traffic	Network densification using small cells	Access to services not necessary through the core network to approach centralized server	×	✓	×	✓	✓
Increase in usage of multimedia package services	Multimedia streaming	Ultra-low latency support	×	✓	×	✓	✓
		Real-time applications support	×	✓	×		
Increase in usage of IoT services	IoT ecosystem deployments	Multiple IoT applications and devices support	✓	✓	✓	✓	✓

In report [6], in densely populated areas of larger cities funding of fixed solutions used within FWA is considered unnecessary with the deployment of 5G access. However, in larger city industrial zones, as well as on highways along which the wired (fiber) infrastructure is implemented, additional funding of fixed infrastructure upgrade can be adequate solution even for the FWA models that can be used to provide both ultra-high capacity and mobility for the real-time communication, especially in the cases of smart environments and autonomous driving, having very high network traffic requirements. In these scenarios, upgrade of fiber infrastructure should be additionally funded by EU funds in order for FWA infrastructure to give its best possible application results, and to enable sufficient capacity and support for high traffic requirements related to autonomous driving. In these cases, it is possible to lease fixed network access to mobile operators to achieve convergence of ultra-high fixed capacities and necessary mobility, also using the converged FWA implementation business model.

Considering the given forecasts which point to further growth in generated mobile and fixed network traffic, the guidelines related to effective busy hour and real-time network traffic management can be additionally defined concerning the deployment of content offloading processes (used in CC, EC, MCC, MEC and FC computing network architectures) or computation offloading processes (used in CC, EC, MEC, and FC computing network architectures), applied to increase data processing speed and improve users' quality of experience with a shorter delay. In general, for the majority of network traffic, there is no added value to route the data through the core network. In this case, the offloading process can be carried out. The content off-loading can be achieved by switching the traffic to use complementary network technologies for delivering data, freeing bandwidth and reducing the total amount of data being carried over a particular communication channel, but also allowing the selection of adequate communication channel for better connectivity. Either the client or operator can set the rules triggering the off-loading action. It is possible to select traffic off-loading at different locations, over open or secured license-exempt access links, and depending on the demanded quality of service. Furthermore, the mobile edge (EC) and fog (FC) based networking architectures enable distribution of data storage at the edge of the network and in that way enable better data processing efficiency and reduced latency to users. Although edge systems scale by adding more resources at a given location, for instance, the small clouds, this approach is not adequate for scaling to support the massive number of devices. Fog system is, on the other hand, capable of shifting computation, networking or storage tasks across peer nodes, or between the cloud and fog, and enables resources pooling. Moreover, the recent developments in mobile edge and fog computing concepts are leveraging small cells as possible computing platforms. Edge computing uses virtualization to distribute computing resources locally. Fog architecture additionally extends edge capabilities by supporting hardware virtualization at each node and allows data processing to be moved to adjacent nodes if some node in the network is unavailable or overloaded. However, although offloading processes increase the efficiency of data processing, they do not always manage to reduce overall systems' capacity consumption. Due to the significant expected increase in the traffic demands, the volume of network resources necessary to achieve a defined level of quality of service also increased. In this context, the selection of effective offloading strategies, and also network infrastructure upgrade must be carried out.

- The results of the conducted analyses presented in Figure 3 forecast further growth in transmission capacity of wireless connections across all frequency bands (bandwidth) usage, as well as growth in the number of installed base stations presented in Figure 4.

According to market indicators given in [4], a continuous growth in demand for the broadband internet access services is present. To meet the increased service demand while maintaining the level of service quality, it is necessary to increase network capacities and access speeds, i.e., to invest in high-speed and high-capacity access networks.

In larger cities, the base station inter-site distance is supported by the need to provide capacity rather than range. This assumes co-location by all operators but in practice there are likely to be many more small cells sites because not all sites will have colocation [6].

Considering the given forecasts which point to further growth in wireless bandwidth usage presented in Figure 3 due to expected significant growth in generated wireless network traffic [4], the guidelines related to effective bandwidth management can be defined concerning network densification processes. The overall increase in bandwidth usage presents the main driver to deploy small cells and to justify the further network densification [6], since the denser networks imply deployment of more edge-oriented services closer to the users (EC and MEC), and this greatly improves the quality of user experience (as well as FC solutions' application) and reduces the network traffic loads on the backhaul links. To identify the point at which small cells become necessary to supplement macro cellular networks, the traffic volume density per allocated unit of bandwidth (Gbps/km2/Hz) is used as the metric. Network densification starts by deploying small cells when the parameter exceeds the 0.02 Gbps/km2/Hz threshold. Furthermore, the need for small cells will be even more necessary in the next generation network settings since the higher spectrum bands need denser network deployments to support larger traffic volumes [6]. While in 4G/LTE networks site densities of up to 30 sites/km2 are common, a 5G network densification process assumes the ultra-dense networks with site deployment densities of 90 sites/km2. According to data presented in [4], the reported number of UMTS and LTE base station sites in 2017 reached 12.440 sites in total. This reflects the joint average site densities of 0,21 sites/km2 in UMTS/LTE networks, which implies that there is a possibility for further network densification, also presumed within the 5G networking concept. This is also visible from the significant growth in the volume of the generated network traffic, i.e., from the fact that the mobile network data traffic for example in 2018, compared to 2017, showed an increase of 103%, as reported in [5], and that further significant network traffic growth is assumed within the next several years [4], as presented in Figure 7. The network traffic growth rates will be even higher once smart environments and solutions become implemented extensively, as pointed out also in [1] and [6].

- The results of the conducted analyses presented in Figure 5 forecast further growth in the number of users of package services.

Given the data from [3] and [5], the operators offer their services to end users in service packages much more than independently, as presented in Figure 9 and Figure 10. The significant increase in the number of 4D packages, i.e., service packages in which operators offer customers in one account services in the fixed and mobile network, is visible. This is possible for fixed network operators that are convergent operators, i.e. the operators that with fixed services can also offer services in mobile networks. The number of users of 4D packages is growing, while the number of users of 2D and 3D packages [4], as well as the number of users of standalone Internet services [5], is reducing.

Considering the given forecasts which point to further growth in the number of users of package services demanding the transfer of heterogeneous data traffic and multimedia streaming, the guidelines related to the effective management of large amounts of multimedia content can be defined concerning the deployment of distributed storage systems (EC and MEC). Unlike in the case of the number of users of stand-alone services, the forecasts point to significant growth in the usage of multimedia package services. The large quantities of multimedia event streams need to be efficiently processed. To keep up with demands set on users' experience, and to overcome the limitations of current radio access networks, the emerging context suggests moving computing capabilities to the edge, as well as the usage of fog computing (FC). The MEC servers implemented directly at the base stations allow faster computing, high-volume media content storage, and hosting compute-intensive applications close to terminal devices. In this way, the MEC systems bring various network improvements, such as the fulfillment of the ultra-low latency requirements, pre-processing of large volumes of data before data forwarding to the cloud, and context-aware services information.

- Finally, the results of the conducted analyses presented in Figure 6 forecast further growth in the number of users of M2M/IoT services.

The traffic demand from non-human usage is just at the beginning of its growth curve [4]. Therefore, new use cases need to be considered. According to [6], connected cars, cameras, and a high density of IoT devices in smart environments will generate significant amounts of new data traffic. Traffic generated by connected vehicles, cameras, and video-based sensors could be a multiple of traffic generated by human users [6].

Considering the given forecasts which point to further growth in the number of users of M2M/IoT services, the guidelines related to the management of network resources within the IoE ecosystems can be defined concerning the deployment of fog and edge solutions. Concerning the ambient intelligence of computing and sensory devices embedded in the environment, smart environments are generating significant quantities of data, and this induces progress towards next-generation data-intensive intelligent systems. With remote sensors installed on machines, components, or devices, different types of data are generated. Concerning the management of limited available network resources and a need for large-scale data classification and clustering processes, the heterogeneous data-rich ecosystems present new challenges in designing intelligent systems. IoT devices have limited computational, memory, and energy resources, so they heavily rely on edge (EC, MEC) and core networks for data handling, processing, and analysis. If data is sent back across a long network link to be analyzed, logged and tracked (CC), that process takes much more time than in the case in which the data is processed at the network edge, close to the source of the data (EC, MEC and MCC). The fog (FC) and edge systems (EC and MEC) enable better options for IoT users and technology providers. By removing the limits imposed by centralized network architectures based on data processing on centralized cloud servers (CC) allows deployments of more distributed and flexible IoT systems.

6. CONCLUSION

Since novel ICT technologies, applications, and services bring many advantages to end-users, ranging from smart homes and smart cars, to smart factories and smart environments, further growth in the adoption of these solutions, as IoT solutions, is inevitable. However, given the accelerated growth in the volume of generated network traffic which is closely correlated to the adoption of advanced ICT solutions, some of the main challenges telecom operators and enterprises working within ICT domain currently cope with are related to the enabling of efficient processing of large amounts of data. Valuable information extracted from a large volume of collected data presents added value that encourages operators and enterprises to experiment with the implementation of novel ICT solutions and to invest in deployments of large-scale IoT initiatives. Therefore, available networking architectures and network settings that enable efficient distribution and allocation of available network resources used for data caching, processing, and computing are examined. Due to requirements related to the performance of novel ICT systems, optimal selection of adequate networking architectures can be achieved based on the analysis of data usage patterns. The processes of effective distribution and allocation of network resources, which significantly impact data processing speed, processing latency and energy consumption can be supported by adaptation and upgrade of existing network architectures.

Therefore, it is necessary to carefully consider all aspects of justification of avoidance of usage of certain funding schemes for network upgrade, proposed for instance in the report analyzing 5G FWA implementation scenarios within [6], and it is important to suggest valid FWA scenarios in which funding schemes for fixed network upgrade are justified and desirable, with regard to their specifics.

In this paper, the analytics of the adoption processes of different telecommunications solutions is conducted for the gathered sets of time series data. The predictive modeling process of broadband services adoption using several types of adoption growth models are given. Alongside standard predictive models, some additional models are used to extend the analysis and additionally back up the results collected by commonly used models. The prediction-based processes of planning, distribution, and allocation of network resources present a crucial step to achieve effective resource planning and network management and to improve the overall system performance. The presented results point to further fast expected growth of overall generated network traffic. Although the telecom operators and ICT enterprises' operation contexts differ and their demands on network infrastructure features may be somewhat different, the guideline that can be drawn from the collection of presented traffic growth forecasts and market estimates includes the fact that the existing network architectures should be developed towards edge and fog networking concepts to enable efficient processing of large amounts of generated data.

It is important to emphasize that the analyses are conducted only for a particular available data sets since a very reduced amount of statistical data is publicly available. In the cases when additional data sets are available, the more precise planning processes can be achieved using the same presented forecast-based approach. Considering the fact that the choices related to network design can be based on more than one parameter, multi-objective decision approaches are planned in future research work.

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