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Generating Demand Functions for Data Plans from Mobile Network Operators Based on Users' Profiles

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Abstract The evaluation of pricing approaches for mobile data services proposed in the literature can rarely be done in practice. Evaluation by simulation is the most common practice. In these proposals demand and utility functions that describe the reaction of users to offered service prices, use traditional and arbitrary functions (linear, exponential, logit, etc.). In this paper, we present a new approach to construct a simulation model whose output can be used as an alternative method to create demand functions avoiding to use arbitrary and predefined demand functions. However, it is out of the scope of this paper to utilize them to propose pricing approaches, since the main objective of this article is to show the difference between the arbitrary demand functions used and our approach that come from users' data. The starting point in this paper is to consider data offered from Eurostat, although other data sources could be used for the same purposes with the aim to offer more realistic values that could characterize more appropriately, what users are demanding. In this sense, some demographic and psychographic characteristics of the users are included and others such as the utilization of application usage profiles, as parameters that are included in the user's profiles. These characteristics and usage profiles make up the user profile that will influence users' behavior in the model. Using the same procedure, Mobile Network Operators could feed their customers' data into the model and use it to validate their pricing approaches more accurately before their real implementation or simulate future or hypothetical scenarios. It also makes possible to segment users and make insights for decision-making. Results presented in this paper refer to a simple study case, since the purpose of the paper is

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to show how the proposal model works and to reveal its differences with arbitrary demand functions used. Of course, results depend on the set of parameters assigned to characterize each user's profile.

Keywords Demographic characterization · Psychographic characterization · User behavior · Simulator · Mobile access service · Study case

1 Introduction

The pricing of mobile data network is the process of assigning a price to the data that travels through the infrastructure of a Mobile Network Operator (MNO). This is a very topical due to the need for alternative pricing approaches that can tackle some of the main problems in the current mobile market, for example, problems that arise from the growing service demand and the infrastructure shortcomings caused by fast growth. Many alternative pricing approaches have been proposed, however, they are rarely evaluated in real scenarios. The evaluation of these approaches is done either analytically [1–3] or by means of simulations [4–16]. As can be seen, evaluation by simulations is the most popular approach. Simulators utilized to evaluate these pricing approaches use models that describe the way users react to services offered by MNOs. According to the state-of-the-art, the most common ways of representing users in these simulators are through utility functions [5–16] or demand functions [4]. Demand functions mainly take into account the price. Utility functions can take into account other parameters that vary according to the proposed approach and the assumptions made in them. However, using utility functions may prove a tricky and subjective way to model users. Each author defines them differently according to assumptions they make and the specific pricing approach and model. For example, Chen et al. [5] used a performance-cost ratio as the utility function taking into account a desired amount of Quality of Service (QoS), the price of QoS, and an efficiency factor of the desired QoS. Lai et al. [11] defined the utility function taking into account the information length of frames, the effective information length of each frame, the speed of the user transferring data, a bit error rate function, the user's signal-to-interference ratio, and the user's power. Loiseau et al. [2] defined the utility in terms of the demand for a shared resource, the maximal utility that users could achieve without shifting any of their demand under conditions of no congestion. Other definitions include the user's valuation of the public good, the loss of utility that the user incurs when shifting a fraction of his demand from peak to off-peak time, a fixed monthly subscription price, a reward proportional to the fraction of the total shifted demand, and the extra price charged to each user for financing the reward. More examples of different utility functions can be found in Sect. 2.

One of the main drawbacks of traditional user models to price mobile data services is that they use predefined standard functions without any clear reason and no experimental data what could be very risky in the process of assigning prices to mobile data services. There are many examples in the literature that confirms it. For example, an exponential one in [17], a logarithmic one, α fairness and shifted α fairness functions in [1], or a natural logarithmic function in [15]. Although these traditional user models are usually accepted, they are established arbitrary and are not based on real data, which may put in doubt the effectiveness of the proposed pricing approaches in a real scenario. Furthermore, these traditional models take into account very few characteristics that describe the users, such as how much money they are willing to pay, their service requirements, their QoS expectancy, etc. Therefore, only very elementary inferences can be made, such as how many users bought a service, how many users with a certain budget bought a product, etc.

For the aforementioned reasons, we propose a simulation model whose output can be used as an alternative method to construct demand functions, instead of assuming these arbitrary functions. In this paper, we are focusing on creating demand functions with the aim to be eventually used in the evaluation of pricing approaches, but this last task is out of the scope of this paper. One of the ways a pricing approach can be evaluated is measuring the amount of revenue it generates for the MNO. This revenue can be calculated by using demand functions that describe the proportion of clients willing to buy a product or service at a given price, which is an aggregate representation of data instead of an individual representation such as utility functions. Aggregated data is a more amenable representation for the users of this approach, namely MNOs, because they will be dealing with huge loads of information.

In this work, our proposed model includes relevant demographic and psychographic characteristics and the utilization of application usage profiles included as a parameter in the profile of the users. In the study case carried out, we used data from Eurostat [18], Sandvine [19] and Roberts [20] to feed the model with the aim of offering realistic values that better characterize what users are demanding. However, other data sources could be used for the same purpose.

We firmly believe the proposed approach is useful because MNOs can use it with their customers' data and utilize it as a way to validate pricing approaches more accurately before implementation. An important feature of the proposed model is that it can be used to simulate future or hypothetical scenarios and obtain insights about the users according to their user profiles, such as demand functions for specific user profiles. These insights can be used later in the decision-making process to create personalized plans and market or sell strategies directed towards specific user profiles.

Results show that when comparing the data generated by our model to the most common demand functions used in the state-of-the-art, these do not fit the demand functions obtained from the data generated by this model.

The article is organized as follows: Sect. 2 mentions some of the models used in the state-of-the-art. The proposed approach is described in detail in Sect. 3. Section 4 provides details about the implementation, mentions the experimentation setup and presents some results. Finally, Sect. 5 introduces some conclusions together with some work that remains to be done and future research ideas.

2 Previous Work

A demand function describes the proportion of people willing to buy a product or service at a given price. The direct relationship between price and quantity sold makes demand functions a very convenient way of modeling users. Moreover, a demand function of a product can depend on variables other than its price. The most common demand functions used in the literature are:

1. Linear. $D(p) = a - bp$ where D is the demand for a product at price p, and $a \geq 0$ and $b \geq 0$ are scalar parameters.
2. Exponential. $D(p) = e^{a-bp}$ where D is the demand for a product at price p, and $a \geq 0$ and $b \geq 0$ are scalar parameters.

$$e - bp$$

3. Logit. $D(p) = N\frac{e^{-bp}}{1+e^{-bp}}$ where D is the demand for a product at price p, $\frac{e^{-bp}}{1+e^{-bp}}$ is the probability of a user buying the product at price p, and b is a coefficient of the price sensitivity.

A list of these traditional demand functions can be found in the book by Talluri and Van Ryzin [21]. Al-Manthari et al. [17] modeled demand using an exponential function that takes into account the price, a demand shift constant and the price elasticity. For Nabipay et al. [3], each user's willingness to pay for a product is given by the product of two independent random variables, w and v, with different distributions. The expected number of buyers who are willing to purchase any particular item at a given price is given by the joint cumulative distribution function of w and v times the number of users.

Utility functions are a way to quantify the satisfaction experienced by the consumer of goods or services. Chen et al. [5] modeled the user as a player in a non-cooperative and a cooperative game between SPs, where the user strategy is to choose the best network according to a performance-cost ratio that takes into account the desired amount of QoS, the price of QoS, and the efficiency factor of the desired QoS. Chen et al. [6] modeled the users by the user's valuation of a connection and the wireless channel characteristics. For Garnaev et al. [1], users are players in a Stackelberg game for a fixed tariff where the user strategy is to decide the size of the network to use. The users' payoff is given by the users' utility, the tariff, and their throughput. Logarithmic, α fairness and shifted α fairness functions are considered as utility functions. Giacomazzi et al. [7] modeled users as agents that negotiate based on their utility function that takes into account the price and the transmission rate. Guerrero-Ibáñez et al. [8] modeled a user by a utility function that takes into account the QoS level provided, the user's preferences for price and QoS, and an evaluation function for the price; and a user connection profile which stores all information about selection decisions made when the user accessed services. Gussen et al. [9] modeled users as players in a non-atomic, non-cooperative game that choose selfishly the service that optimizes their individual satisfaction according to their utility in function of a user's class, the experienced QoS, the

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network state and the price of the service. Lai et al. [11] modeled users as players in a non-cooperative game where each player tries to maximize his/her utility in function of the information length of each frame, the effective information length of each frame, the speed of the user transferring data, a function of bit error rate, the user's signal-to-interference ratio, and the user's power. Lai et al. [10] extended this work considering more than one base station. Lee et al. [12] modeled users by the number of tokens they have according to the amount of money they pay monthly and their utility for an application as a function of the level of congestion for a level of service. For Ren et al. [13], a user's utility is given by the subscription price charged by the Network Service Provider (NSP), the QoS provided, and the user's valuation of QoS. Ren and van der Schaar [14] modeled a user as a player in a non-cooperative game whose reward is defined by the net utility as a function of the signal-to-interference-plus-noise ratio and the price charged for relays to users utilizing their resources for their transmissions. For Song et al. [15], every user has a utility function that reflects the degree of satisfaction when transmitting with a data rate during a time slot, the price charged, and the admitted rate. They consider a natural logarithmic function for this.

Ha et al. [22] modeled users according to their willingness to defer their data usage as a function of the time deferred, the discount offered, a patience parameter and a patience index.

For Parris et al. [16], users arrive according to a Poisson distribution and are modeled by three parameters: (1) Class: each class uses a different percentage of total network bandwidth. This is modeled by a binomial distribution. (2) Duration: connection times are exponentially distributed. (3) Money: users are poor or rich, each having a fixed amount of money. This is also modeled by a binomial distribution.

3 Simulation Model

As we already mentioned, traditional user models use standard functions that are most probably arbitrary and not based on real data. The proposed model can use real data MNOs as input and transform them through the simulation process into data that can be used to construct more realistic and accurate demand functions.

The general simulation model (Fig. 1) describes the mobile market, in which MNOs offer services to users. In the model, user modules interact with MNO modules. Figure 2 shows the interaction of a user with MNOs. User modules define the behavior of users that depend on the user profile. This user behavior refers to the way the user decides which data plan to subscribe and how the user evaluates the received service that is key to decide continue with the subscription or not. MNO modules represent certain characteristics of MNOs. In particular, an MNO module can represent the allocated resources for the service, the data plans it offers to users and the pricing approach it uses. Each offered data plan has a particular price, an assigned data cap, a cost of data charged to users whenever they exceed their plan's data cap (overage charge), an amount of resources assigned to each plan and a subscription period for which the user is bound to the data plan. MNOs' behavior

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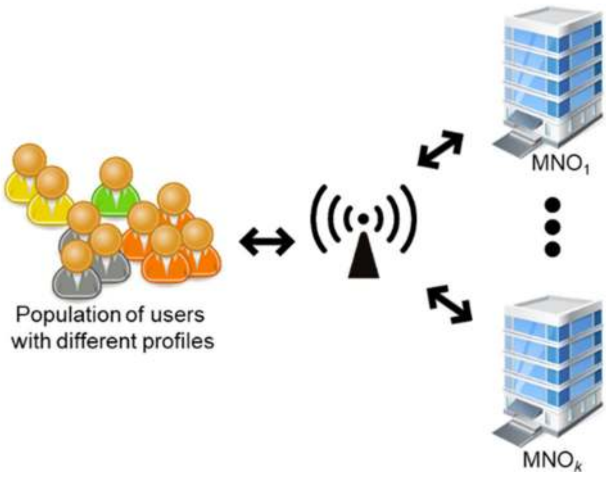

Fig. 1 General simulation model (mobile market)

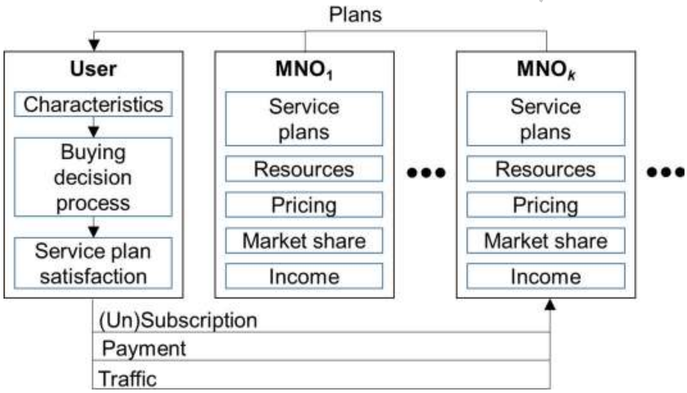

Fig. 2 Proposed simulation model

can be implemented according to different pricing or any other techniques or approaches from the state-of-the-art, but this is out of the scope of this work. Since the focus of this work is in the user module, in the next subsections, we will explain it in detail.

3.1 User

Users are defined by their profile that is made up of demographic and psychographic characteristics and application usage profiles. Each user profile will influence the behavior of each user. Therefore, users generate traffic or decide the MNO that they subscribe (i.e., buying-decision process) depending on those profiles. In the following subsections, the user model will be detailed.

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3.1.1 User Profile

A user profile is defined by a set of characteristics, where some are independent and others depend on the value of other characteristics. Figure 3 shows these characteristics and their relationships or dependencies. We define two main characteristics that are budget and application usage profile, but the user profile can include other ones that would influence the behavior of the user. The budget was chosen because it is a restrictive variable when buying any service or product. For this work, this is of great importance because we are trying to model purchase and post-purchase behavior. From this behavior, we will obtain the simulator output data used to construct the demand functions.

The profiles can be created by using MNOs' data about their users or by using statistical data. In this case, we use Eurostat data where income varies on average according to age and sex. Income has an effect on the budget a person allocates for different purposes. Based on this, we make the assumption that budget depends on age and gender. Assimakopoulos [23] segmented mobile Internet customers into classes based on demographic characteristics, payment models, and attitudinal characteristics. Across segments, it can be seen that mobile service expenditures were linked to age. This was found in [24] too.

In addition, we explicitly chose gender and age because they appear consistently as variables in research works and reports that relate people's characteristics with technology and the mobile market, such as in [23–31]. Age is widely used as a demographic variable to characterize the adoption of technologies between two or more consumer groups, like in [26–28]. In this work, we refer to this affinity for technology as technophilia. Sell et al. [32] found that different attitudes towards technology define behavior regarding the use of mobile applications. Im et al. [33] obtained similar results with other types of technologies. Quorus Consulting Group [30] and Ernst & Young Global Limited [24] showed how mobile devices and services usage varies among different age groups. This led us to relate technophilia to application usage profiles.

We propose the utilization in the user profile of application usage profiles, which we define according to the type of applications that users use as shown in Table 1.

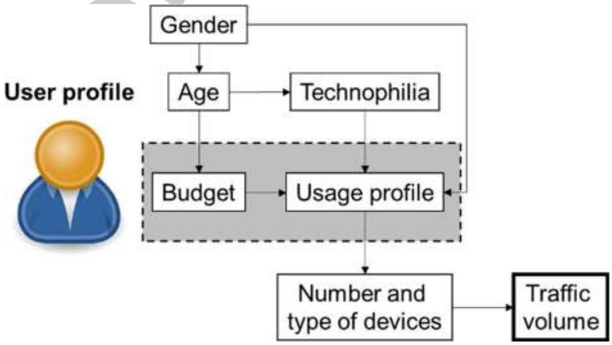

Fig. 3 User profile characteristics and dependencies among characteristics

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Table 1 Application usage profiles

	Profile 1	….	Profile n
Application 1	Mean data events per period	…	Mean data events per period
…	…	…	…
Application n	Mean data events per period	…	Mean data events per period

Different applications generate, on average, different amounts of traffic. Some examples are shown in Table 3. Thus, a gamer usage profile would mainly include online gaming and social media applications. The amount of data users require to satisfy their needs has an impact on the purchase and post-purchase behavior. Findings by Kumar and Helmy [25], Papaioannou et al. [28], Peslak et al. [29], and Shi et al. [31] showed that genders have different affinities for different types of applications. Rocha et al. [34] showed that customer profiling can be of crucial importance to several networking tasks, such as resource management, service personalization, and security.

The type of device used also affects the generated traffic volume. Some applications and services offer optimized content according to the type of device used. It is because of this that we take the type of devices used into account. We propose to relate applications to devices as shown in Table 2.

The process of building a user profile is shown in Fig. 3, following the dependencies depicted in the figure as if it were a low diagram. The following are the steps for building a user profile:

1. Gender: It is a binary characteristic and is assigned according to the probability of being male or female.
2. Age: Two age distributions are used to assign age, one for males and another for females.
3. Budget: It is assigned as a function of age and gender. We used an age function to determine the mean budget according to gender. We then obtained a random variable using a wealth distribution and scaled it taking as references the mean wealth distribution and the mean budget obtained from the age function according to gender.
4. Technophilia: It is another binary characteristic and the probability of being or not technophile is determined using an age function.
5. Application Usage Profile: It depends on budget (since each application consumes different traffic volumes that requires distinct data caps), technophilia

Table 2 Application and devices

	Device 1	…	Device n
Application 1	Data amount	…	Data amount
…	…	…	…
Application n	Data amount	…	Data amount

and gender. Discrete probability distributions are defined for each gender and technophilia values that describe the probability of each application usage profile. The application usage profile is chosen using these probabilities, only taking into account the affordable application usage profiles according to the budget.

6. Number and type of devices: Each type of device is given different probabilities according to the application usage profile, arranged in decreasing order according to these probabilities. These probabilities are added until the value of a random variable is exceeded. Those devices whose probabilities were added are chosen.
7. Traffic volume: It is decided distributing data events randomly among devices and relating each event to an amount of data according to the device. The number of data events in a period can be obtained using a distribution that takes the mean data events as a parameter.

3.1.2 Buying-Decision Process

In this model, we follow the buying-decision process introduced by Dewey [35]. This process defines the way users decide the MNO and service plan they subscribe. Also, the process defines how the user evaluates the subscribed service plan to encourage the user to keep the current service plan or look for a different one. The buying-decision process consists of five stages:

1. Problem/need recognition: At this stage, users are not subscribed to a data plan or have not decided to continue with their current subscription.
2. Information search: The user first has to find out which MNOs are available in the market and the current plans they are offering. In this work, this will be decided based on the MNOs' market share. The first MNO is selected randomly using a roulette wheel selection and the subsequent ones depending on whether the market share is greater than a random threshold.
3. Evaluation of alternatives: Users will evaluate service plans according to some criteria dictated by their user profile characteristics (budget and traffic volume) and current state (new/old user), and discard those that do not meet these criteria. In this work, users discriminate plans based first on the price according to their budget and then based on the data cap of the plan. Users that have been subscribed before to a data plan will have an idea of the amount of data they consume, so with this idea, we use the traffic volume generated by users during the last billing period to discriminate plans based on each plan's data cap. Users that have never been subscribed to a data plan will not have an idea of how much traffic they will generate during a billing period. Bearing this in mind, we suppose that new users only discriminate plans based on their cost. The flowchart of this stage is depicted in Fig. 4.
4. Purchase decision: Users will compare the ser-vice plan alternatives based on their characteristics and choose the one that best satisfies their needs. In this work, users will choose plans differently depending on whether they are

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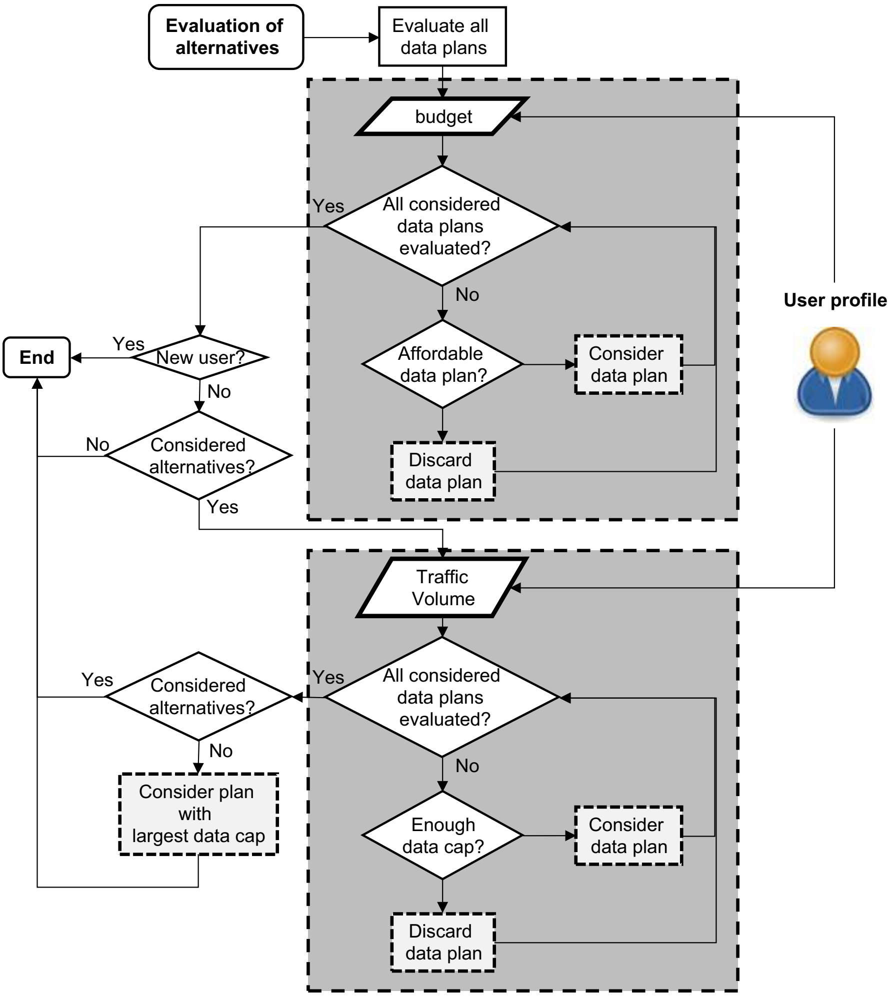

Fig. 4 Evaluation of alternatives (user module)

technophiles or not. If users are not technophiles, they will choose based on price; and if there is a tie between two plans, users will choose based on the data cap. If users are technophiles, they will choose plans based on the data/price ratio. If users have a bad opinion of the last data plan they were subscribed to, they will choose plans based on price and data cap. If there are no plans with an adequate data cap, the user will choose the data plan with the greatest data cap. The flowchart of the purchase-decision stage is shown in Fig. 5.

5. Post-purchase behavior: At this stage, users will evaluate the service plan they are subscribed to. This evaluation will encourage the user to keep the current service plan or look for different service plan options. At the end of the billing period, users will evaluate the plan they are subscribed to based on two factors: exceeding their budget and exceeding the plan's data cap. If they exceed the

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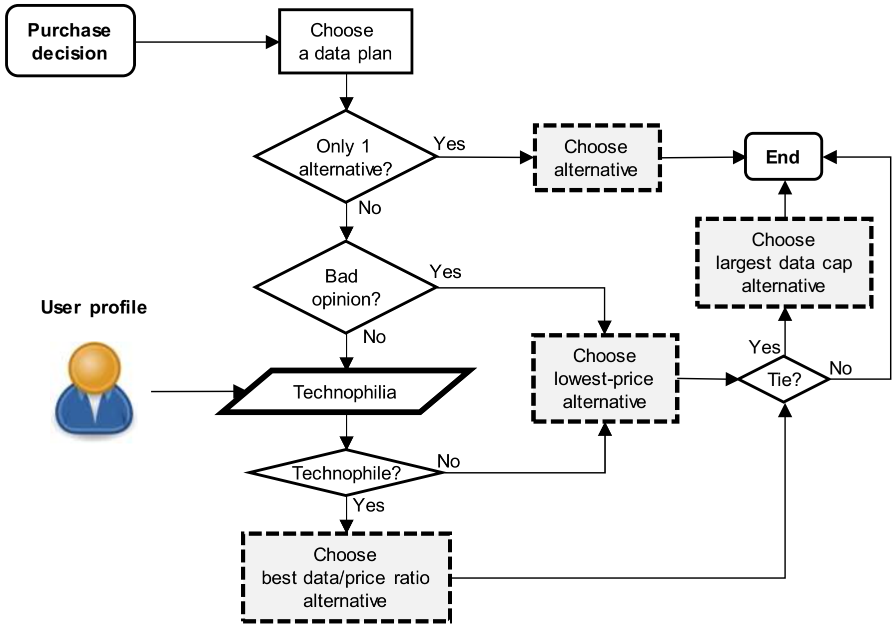

Fig. 5 Purchase decision (user module)

budget or the plan's data cap, they will increase their bad opinion (dislike) about the current data plan and they limit they data consumption on the next billing period. Otherwise, they decrease their bad opinion about the plan and they allow more data consumption. At the end of the subscription period, the user will recognize a problem with the current data plan if the satisfaction with

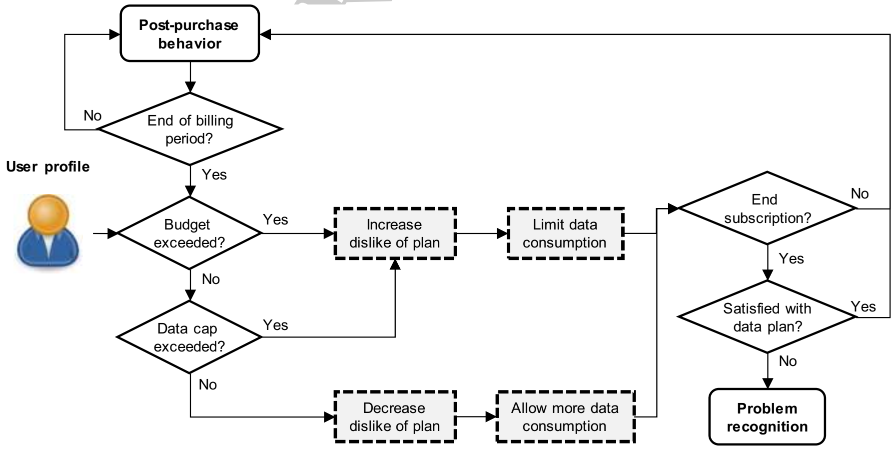

Fig. 6 Post-purchase behavior (user module)

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the data plan is not enough. Figure 6 shows the flowchart of the post-purchase behavior that users exhibit in this work.

4 Study Case

4.1 Simulation Framework

The OMNeT++ simulator by OpenSim Ltd [36] was chosen as the framework to implement the proposed approach, since it provides adequate infrastructure, tools for writing discrete-event simulations and offers a generic architecture that can model and simulate any system that can be mapped into entities communicating by exchanging messages. Models are made up of reusable components called modules. Modules can be combined to form compound modules. Modules may have parameters that can be used to customize module behavior and/or to parameterize the model's topology. Modules at the lowest level of the module hierarchy are called simple modules, and they encapsulate model behavior. Simple modules are programmed in C++ and make use of the simulation library. We use two simple modules to model users and MNOs.

The simulation framework is shown in Fig. 7. First, in the simulation initialization, characteristics for users are assigned according to the distributions used as parameters. These distributions are inferred from statistical data from Eurostat or other data sources, to adjust the users' profiles to the real world. An MNO using this simulation model could use its own data about their users. MNO characteristics are also assigned. Implementation details of the process of assigning characteristics to users were mentioned in Sect. 3.1.1. After the initialization, the simulation goes to the Users-MNOs interaction stage, in which users apply the buying-decision process defined in Sect. 3.1.2 to interact with MNOs. Finally, the simulation finishes when the demand for each MNO is considered stable and the data is analyzed. In the following subsections, we define the implementation of these three stages for a simple study case to illustrate how the model could be used.

4.2 Study Case Initialization

The main objective of this work is to compare the data generated with our model to the most common demand functions used in the state of the art. For the purpose of

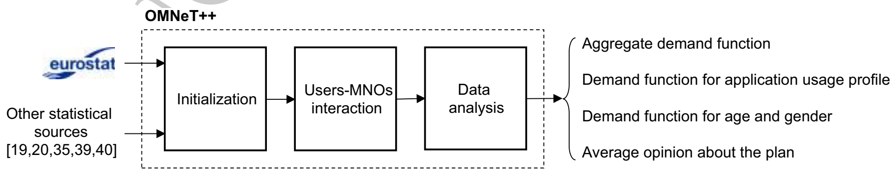

Figure 7: Simulation framework

Fig. 7 Simulation framework

presenting a simple example of the use of the proposed model, a scenario with the following characteristics is considered:

- One MNO offering one data plan with a data cap of 5 GB and a fixed flat price.
- An overage charge of 5 Eur./GB.
- The user population is set to 10000 users.
- The billing and subscription times are set to 30 days.
- Simulation time of 720 days.

This scenario is used for prices ranging from 0 to 100 Eur., with an incremental step of 1 Eur.

4.2.1 User Parameters

For the experiments carried out, data from Eurostat were used, whenever possible, as input for the model. For other characteristics and parameters where data from Eurostat could not be used as input, distributions and values we deemed appropriate according to findings already mentioned in Sect. 3.1.1 were used instead. A discrete distribution that describes the share of the female and male population was created using Eurostat 2014 data. Two discrete distributions were created that describe the age distribution of individuals with a certain gender. Eurostat 2014 data were also used to create the aforementioned age distributions. As already mentioned in Sect. 3.1.1, two functions are used to define a user's budget: a wealth distribution and a function that relates age to budget.

The wealth distribution used in this work was obtained by finding the distribution function best fitting the maximum monthly income percentile data from 2014 reported in Eurostat. Several distributions were fitted to these data, but after many approaches, it was found that the Gamma–Gompertz distribution, reported in [37], was the best fit. The Gamma–Gompertz distribution parameters that gave the best fit with these data were $s = 0.2782$, $b = 24.56$ and $\beta = 52.72$.

Data reported in Eurostat [18] in 2014 regarding mean income for age intervals according to gender were used to ob-tain a function that relates age to budget. The function $meanbudget\ (age) = a * exp\ (b * age) + c * exp\ (d * age)$ was obtained using MathWorks MATLAB [38] curve-fitting tool using Eurostat data as input. Parameters for this function for males are $a = -0.2411$, $b = 0.07355$, $c = 61.79$ and $d = 0.01057$; for females these parameters are $a = 0.9996$, $b = 0.06179$, $c = 56.94$ and $d = 0.01395$. Data for computer and Internet usage in different age intervals from 2014 reported in Eurostat were used to obtain an age function to calculate the probability of being a technophile. The function $probabilityTechnophilia = (p1 * age2 + p2 * age + p3)/(age + q1)$ was also obtained with MathWorks MATLAB curve-fitting tool using Eurostat data as input. Parameters for this function are $p1 = 0.02287$, $p2 = 2.061$, $p3 = 6.4 \times 10 - 3$ and $q1 = 14.88$.

Many application usage profiles could be considered, but for simplicity in their study, six representative ones are taken into account in this implementation. They are shown in Table 3: moderate use users, users that play online games, users that

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Table 3 Implemented application usage profiles

	Moderate	Gamer	Social	DJ	Worker	Movie
Email	30	150	150	150	2400	150
Music stream (min)	0	0	240	1200	0	240
Music download (song)	5	20	30	180	10	30
Video stream (min)	12	120	120	600	0	1800
Video call (min)	0	0	20	0	240	0
Audio call (min)	0	0	120	0	480	0
Surf web (pages)	150	500	1500	600	600	600
Social media (posts) w/photo)	600	1500	4500	1500	1500	1500
App/game download	5	50	20	20	5	20
Online gaming (min)	0	3600	0	450	0	450
Instant messages	600	600	12000	1500	1500	1500
File download	5	5	5	5	5	5

use the service for work-related activities, users that are very active in social networks, users who mainly listen to music (DJ) and users who mainly watch videos (movie). The shares of each application usage profile in the population are as follows: moderate 26%, gamer 34%, social 21%, DJ 8%, worker 7% and movie 4%. These values are based on the share of users by data plan according to their data cap reported by Roberts [20], bearing in mind that each application usage profile has a related mean data generation. Sandvine [19] reported the Peak Period Aggregate Traffic Composition for Mobile Access in Europe. These data were taken into account when filling in Table 3. As already, mentioned users can have more than one type of mobile device. In this work, the device probabilities considered for each application usage profile are shown in Table 4. Finally, each event data amount according to application and device is shown in Table 5. This table was compiled with data from MNO websites in different countries, such as in [39, 40].

As mentioned in Sect. 3.1.2, in the post-purchase behavior users will increase or decrease their bad opinion about the plan they are currently subscribed to. The increment is made in an additive manner, where the increment step is set to 0.1. The decrement is made in a multiplicative manner, where the step is set to 0.6. The

Table 4 Device probabilities for application usage profiles

	Smartphone	Tablet	Mobile computer
Moderate	0.80	0.10	0.10
Gamer	0.10	0.80	0.10
Social	0.25	0.25	0.50
DJ	0.50	0.40	0.10
Worker	0.80	0.10	0.10
Movie	0.10	0.80	0.10

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Table 5 Applications and devices

	Smartphone	Tablet	Mobile computer
Email (no attach 75%, w/attach 25%)	20 KB/300 KB	20 KB/300 KB	20 KB/300 KB
Music stream (min)	1 MB	1 MB	1 MB
Music download (song)	7 MB	7 MB	7 MB
Video stream (min)	5.1 MB	5.1 MB	15 MB
Video call (min)	12 MB	12 MB	12 MB
Audio call (min)	2 MB	2 MB	2 MB
Surf web (pages)	1 MB	1 MB	2 MB
Social media (posts w/photo)	350 KB	350 KB	500 KB
App/game download	4 MB	5 MB	30 MB
Online gaming (min)	85 KB	85 KB	85 KB
Instant messages	15 KB	15 KB	15 KB
File download	4 MB	4 MB	30 MB

maximum bad opinion index is set to 1, so when the bad opinion reaches this value; users will start considering changing plans. The initial and minimum value is 0 when users are completely satisfied with their data plan.

4.3 Data Analysis

In this section, some results are analyzed. In this sense, it is shown how an aggregate demand function can be constructed from the data obtained with the simulator using the proposed model and how to obtain demand functions for specific groups of users based on the user profiles and lately are compared to the most common demand functions according to [21]. The linear, exponential and Logit functions were fitted to the data generated by the simulation model to show graphically and statistically that these functions could not fit the demand functions generated by the simulator using the proposed model, which is more realistic. The results presented are referring to the aggregate demand functions, the average opinion about the plan and the demand functions for different application usage profiles.

4.3.1 Aggregate Demand Function

The aggregate demand function obtained from the simulation model output data is represented in Fig. 8. Demand is obtained by measuring the mean number of customers subscribed to the MNO. Even though, the exponential demand function is the best fitting one according to Table 6 and does it so, in the tail of the demand function obtained from simulation output data, the first part of the demand function obtained from simulation output data does not fit with any of the three most common demand functions.

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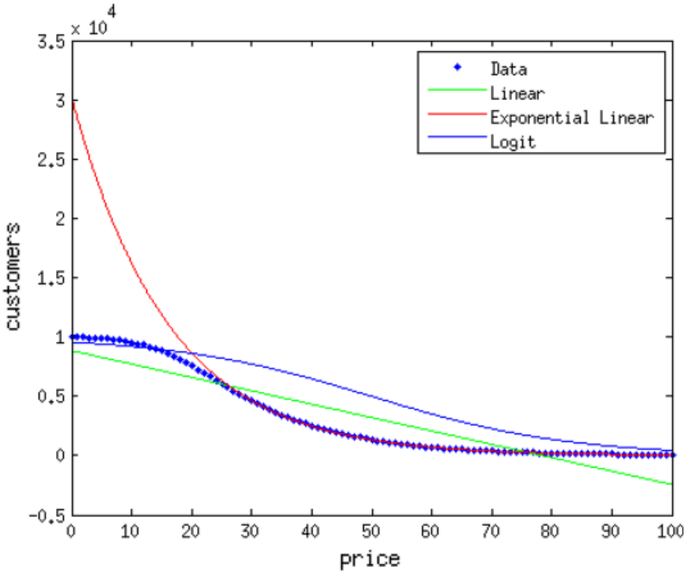

Fig. 8 Aggregated demand function

4.3.2 *Demand Functions for Application Usage Profiles*

In this section, demand function was constructed from output data generated by the simulator grouping users according to one characteristic. In this case, the grouping characteristic used was the application usage profile that describes the type of applications users use and how much they use this application.

Table 6 shows statistical information about the goodness of fit of the three demand functions most commonly used in the literature. Two statistical measures are used to compare the three demand functions with the empirical data: R-squared (coefficient of determination) and Root mean square error (standard error). In the case of the Root mean square error (standard error), smaller values mean a better fit. For the other statistical measure, a bigger value means a better fit.

In Fig. 9, the demand function for moderate users is shown. It can be seen here that the exponential function fits well with the simulator output data, but deviates from the simulator output data in the first part of the function. It can also be seen that the linear function fits the simulator output data in the tail. Table 6 confirms that the exponential function is the one that best fits the simulator output data. Similar behavior can be seen for Gamer and Social users, with the only difference that these types of users are associated with a higher budget and the demand starts to descend at a higher price than for the moderate users.

In Fig. 10, the demand function for Movie users is presented. The demand function from the simulator output data is similar for DJ, Worker and Movie users. This can be explained as these users are associated with greater wealth and are willing to pay more for the data plan offered by the MNO in this scenario. It can be seen in Fig. 10 and in Table 6 that the Logit demand function fits well with the

Table 6 Goodness of fit

Application usage profile	Function	R-squared (coefficient of determination)	Root mean square error (standard error)
Total	Linear	0.821053	1524.925767
	Exponential	0.997967	162.526126
	Logit	0.506045	2520.857226
Moderate	Linear	0.720568	444.548681
	Exponential	0.998423	33.399030
	Logit	0.059630	811.424048
Gamer	Linear	0.729057	590.352782
	Exponential	0.998106	49.355813
	Logit	0.187907	1016.934710
Social	Linear	0.771061	444.291146
	Exponential	0.996150	57.613844
	Logit	0.502559	651.622391
DJ	Linear	0.872813	128.095155
	Exponential	0.810040	156.546280
	Logit	0.992309	31.341004
Worker	Linear	0.868029	108.214086
	Exponential	0.811799	129.227747
	Logit	0.994526	21.929361
Movie	Linear	0.882281	50.091382
	Exponential	0.729282	75.962179
	Logit	0.929590	38.545397

simulator output data for these three users. In the first part of the function, where the majority of users are willing to pay for the service, and in the tail of the function where the users are not willing to pay for the offered service. However, the part where the Logit function and the simulator output data start to decrease does not match particularly well.

It can be seen in these demand functions that according to each application usage profile, which can be associated with a degree of wealth, the majority of the population of each application usage profile is willing to pay for the offered plan up to a point where the number of users that can afford it starts to decline. It can also be seen that in those application usage profiles that generate less data, and which are affordable for more people, there is a greater concentration of population. It can be seen that the exponential function fits quite well for the application usage profiles that are affordable for more users, and as the application usage profiles are associated with a higher degree of wealth, the exponential function fits less well. It can also be seen that more users with profiles that generate more traffic, and which are associated with higher budgets, can afford to buy products even when their price

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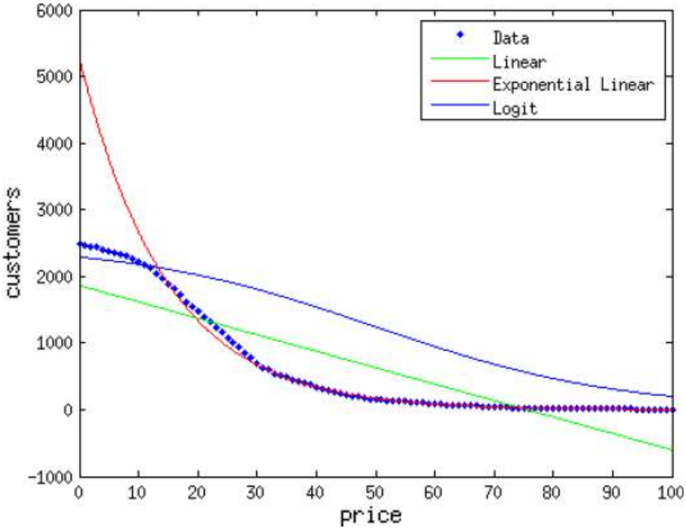

Fig. 9 Moderate users demand function

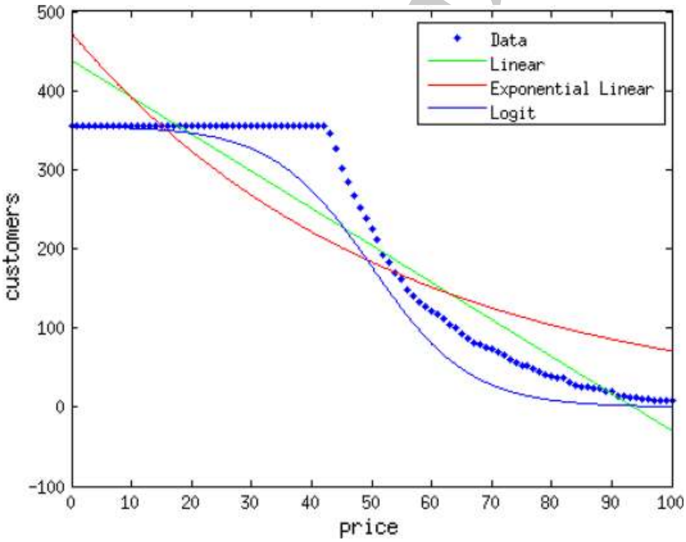

Fig. 10 Movie users demand function

is higher. These are just some of the inferences that can be made using only the application usage profile characteristic.

4.3.3 Demand Functions for Age and Gender

Figures 11 and 12 show the demand functions from the simulator output data for male and female population with different ages. Figures 11b and 12b show the

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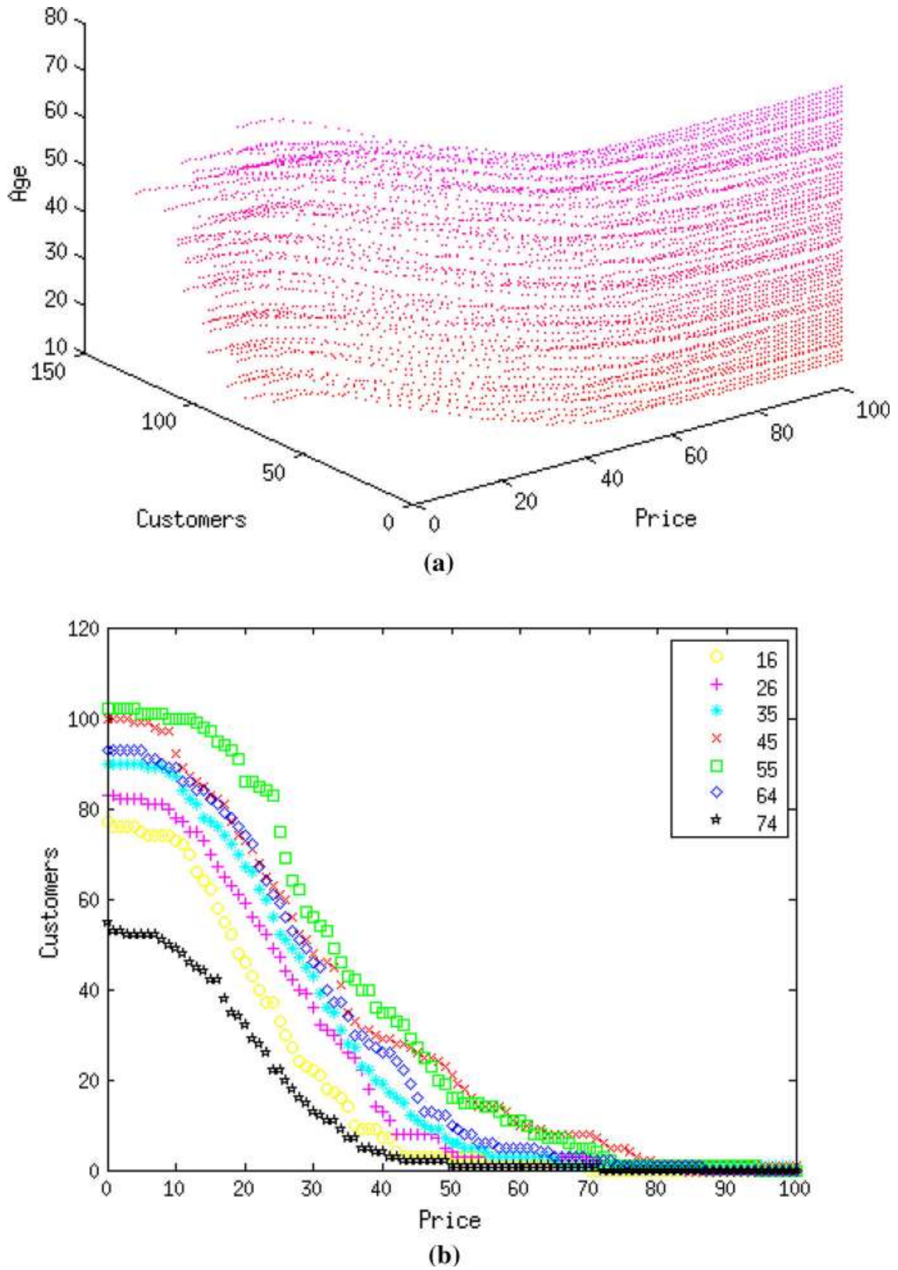

Fig. 11 Demand functions of female users with varying age. **a** Demand functions of females from 16 to 74 years, **b** price versus customers axis, showing 7 different ages

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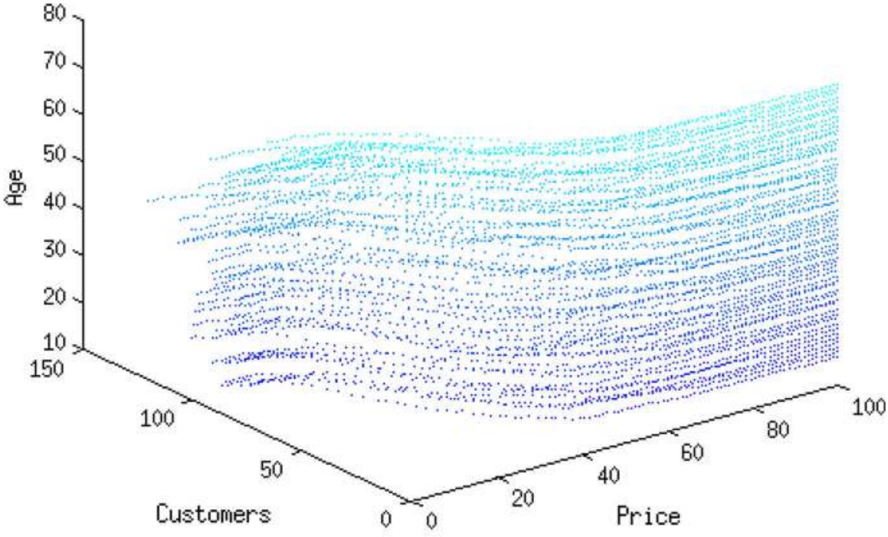
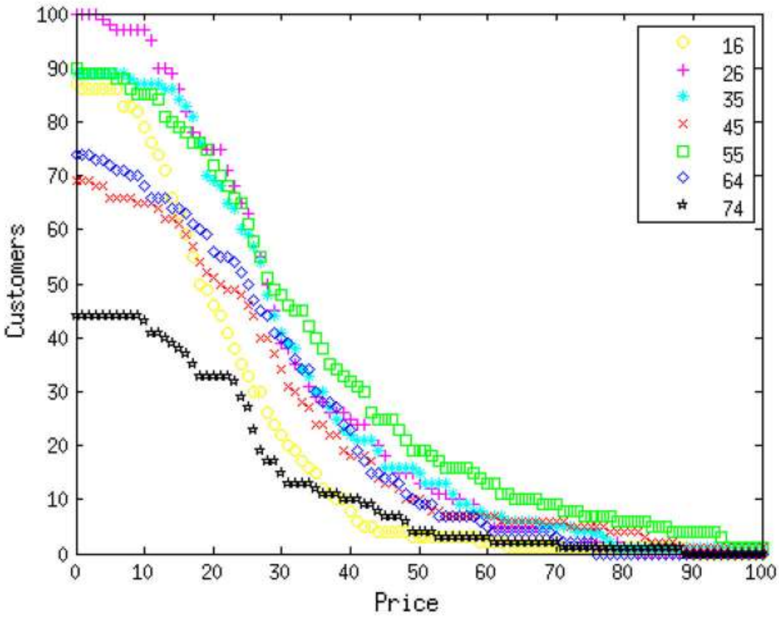


(a)



(b)

Fig. 12 Demand functions of male users with varying age. **a** Demand functions of males from 16 to 74 years, **b** price versus customers axis

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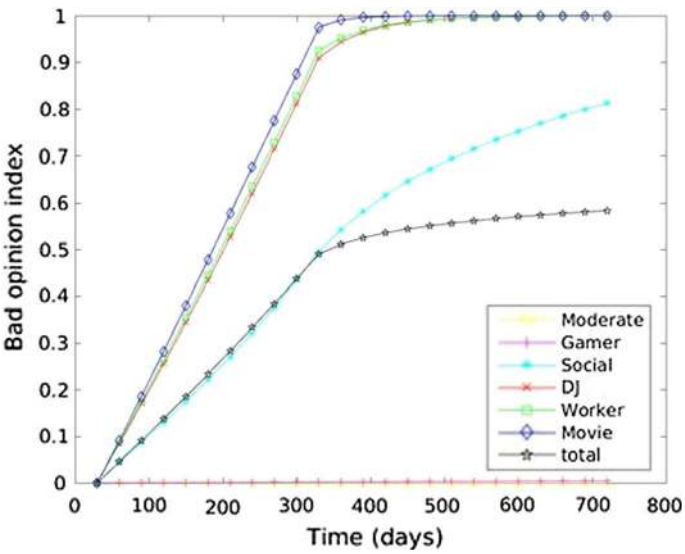

Fig. 13 General opinion about plan offered

demand functions of users with different ages, each line with a different color corresponding to a certain age. Just seven of the demand functions are shown to enable a better understanding of them. The demand functions have more or less the same shape but with different points where the demand starts to decrease and in some cases a different rate of decrease. This has to do with people's budget being a function of their age. In Figs. 11a and 12a, the demand functions of people grouped by sex and age are shown in 3D figures. In these 3D figures, the demand functions according to the user's age can be seen, with lighter colors corresponding to older users and darker colors corresponding to younger users. As already mentioned, the number of people of a certain age and their budget determine the shape of the demand functions. Few more comments can be made when working within a monopolistic scenario with just one data plan to select from. Users' attitudes towards the data plan and the MNO and the way users make their decisions to buy a data plan are not particularly significant because they do not have other options and have to settle for the only option they are given.

The inferences mentioned in the previous paragraphs are just some of those that can be made from the data generated by the simulator by grouping users according to two characteristics. More inferences can be made using other combinations of characteristics included in the model proposed here.

4.3.4 Average Opinion About the Plan

The opinion about a plan is also important. This tells MNOs how happy their customers are with the plans they are offering. The opinion measured in the simulator represents a bad opinion about a plan (as mentioned in Sect. 4.2.1). In this scenario where an MNO is offering a single plan, the users' opinion is a very

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interesting aspect to focus on, since the demand function will mostly be influenced by the users' budget because they have no more options to choose from. The users' opinion shows that there is a degree of dislike in the population since there are some users that have to restrict their traffic because the data cap is not enough for their application usage profile and some may be exceeding their budget at times. This indicates that users given the opportunity to change to another plan would most probably do so. Figure 13 shows that at the beginning the dislike grows more quickly due to users with application usage profiles that demand a larger data cap. Then at a point, the dislike starts to increment more slowly, due to users exceeding their budget at certain times, which is not normal in their application usage profiles. In fact, this figure shows how 'fast" on average different usage profiles increase their dislike of the plan offered.

5 Conclusions

Traditional user models utilize standard predefined demand functions that are most likely arbitrary and unrealistic because they do not take into account fundamental characteristics of the users such as their user's profile which includes their applications usage profile. To improve this issue, this paper presents a simulation model that generates appropriate data to construct more realistic demand functions. These functions could be used further to assign prices to the mobile data services, but this task is out of the scope of this paper. We believe these demand functions are more representative of real data and eventually could help to price more accurately MNOs data plans. In the study case we carried out, Eurostat data was used as input for the model with the aim of using realistic data. MNOs can use other data sources for the same task, for example, data from their customer databases, creating in advance some demand functions elaborated from the profile of their users. The inclusion of demographic and psychographic characteristics in the model gives the opportunity to obtain more insights and to make other inferences about pricing approaches.

In the study case, we have presented demand functions constructed from the generated data by the proposed model and they have been compared to other traditional or predefined demand functions. From this comparison, it could be seen that the most common demand functions according to [21] do not fit the demand functions constructed by the simulator output data. Although, in some cases, the demand functions fit the simulator output data to some degree, none of the demand functions analyzed, fits well in all cases. This fact shows the differences and benefits of our proposal that takes real data as input to generate data through simulation from which demand functions are obtained, instead of supposing predefined demand functions.

Two 3D plots in Figs. 11a and 12a show the relationship between three variables: demand, price, and age. More specifically, these subfigures show how the population distribution, the budget function, and the attitude-towards-technology function have an impact on the demand functions created. However, this model could be used in a more flexible way, including other variables or characteristics

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that can be combined in different alternatives to obtain new insights that can be used to evaluate or validate distinct approaches according to the characteristics of each segment of the population.

We believe that is more reasonable to obtain a priori unknown demand functions, since it allows us to understand how is the behavior of the users, including some assumptions of the demographic and psychographic characteristics they could present. From these data, by using our model it is possible to simulate the interaction between users and MNOs in markets and lately obtain the demand function. This procedure is more constructive and flexible than to assume traditional demand functions without any type of justification of the proposed values, and of course, far away with real market data. The proposed approach is useful for MNOs because they can use the already available data about their customers to feed the simulation model and with them generate data from which more exact demand curves are obtained. Eventually, this would allow MNOs to evaluate more reliably pricing approaches before they decide to implement in reality. Furthermore, using this model lets MNOs focus on specific subsets of users to get advanced insights that could be used later in the decision-making process, to create marketing and sales strategies directed towards specific users. Likewise, the proposed approach can be used to model users in other scenarios where providers are offering other kinds of services or goods.

Using similar scenarios and same parameters but with different data cap included in the data plan were also carried out. In this case, the obtained results were similar as the ones presented in this paper and there were not included in this work. This could be because in this case there is only one MNO that offers a single data plan, thus leaving users with no other option.

This is our first step in the effort to define, in a more natural way, the user response to prices, avoiding to use standard demand and utility functions that are not reliable in the majority of the cases. Although we make some assumptions and there is still further work to do with respect to defining the user profiles and their evolution more accurately, we sincerely believe that this paper is a good start towards defining a more precise and descriptive demand functions. With this idea in mind, future work can include refining the model and studying the way that varying the number of characteristics or using different ones could affect the output of the model. Other research could include, working on more complex scenarios, such as an operator offering several data plans, several operators offering the same data plan, or a combination of both; and finally, working in selected scenarios (selected user profiles) that take into account how the demand function evolves.

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