The final publication is available at Springer via http://dx.doi.org/10.1007/s11276-016-1334-8

A social model for the mobile market based on customers profile to analyze the churning process.

Mario R. Flores-Méndez[a], Marcos Postigo-Boix[b], José L. Melús-Moreno[b]

[a]*Department of Signal Theory and Communications, Universitat Politècnica de Catalunya, 08034 Barcelona, Spain*
[b]*Department of Telematics Engineering, Universitat Politècnica de Catalunya, 08034 Barcelona, Spain*

Abstract

In a high saturated market where a variety of MNOs (Mobile Network Operators) offer relatively homogeneous wireless technologies and services in the same area or region, customers have the freedom to choose the service based on any factor they deem important. In addition to this, mobile number portability contributes to a phenomenon called churning where customers migrate from one Mobile Network Operator (MNO) to another. Churning impacts not only the network design but also the pricing methods adopted by MNOs and, and hence their revenue. It is because of this that MNOs try to reduce churn through retention campaigns detecting potential churners before they leave the service. The mainstream approach to churn prediction considers each customer individually. Preliminary studies have shown that members in the social circle of a subscriber also influence the subscriber to churn. Thus, systems that take social aspects into account poses an emerging theoretical challenge with potentially great practical implications. The state of the art has focused on proposing methods to identify churners based on data mining techniques, however these techniques doesn't always offer clear explanations for churn reasons. Instead, we use a technique called Agent-Based Modeling to model customers in the mobile telecommunication market and assess the effects of customers characteristics and behaviors on such market. We propose a model that includes some relevant demographic and psychographic characteristics and the utilizations of usage profiles to describe customers individually. We propose to take into account social behavior. We modified an existing social network generator algorithm to take into account the user profiles when creating a connection. We show through experimentation that using our approach, compared to not using social networks or homophily, yields better results.

Keywords: social network, homophily, customer profile, churn, customer model, wireless network

1. Introduction

Technology advances made in wireless telecommunications over the past decades have made them more affordable to people, leading to penetration growth in this market in both developing and developed countries Chau (2010); Str (2009); ITU (2013). In a market, where a variety of MNOs offer relatively homogeneous wireless technologies and services in the same area or region, customers have the freedom to choose the service based on any factor they deem important. Because of this, MNOs can no longer rely only in offering good QoS (Quality of Service) and novel services, but also have to resort to aggressive customer-centric targeted marketing campaigns, special offers, bundling services, among other strategies in order to position themselves in the market and make a profit. In addition to this competition among MNOs, number portability and the ease and rapidity of it have resulted in a phenomenon called churning where customers migrate from one service provider to another looking for a service that better satisfies their needs.

Customers churn for a variety of reasons. Lon (2012) cites competitive pricing, network service quality, discounts, and promotions as some of the primary reasons. Other reasons for customers churn are: availability of services and devices, marketing campaigns, tenure which is associated with loyalty, engagement with service and complaints outcomes or quality of customer service.

Churning impacts not only the network design but also the pricing methods adopted by MNOs, and hence their revenue. It is because of this that MNOs try to reduce this phenomenon as most as they can. One of the ways MNOs are doing this is through innovative retention campaigns, since it is very well known that the costs of acquiring new customers are higher than to retaining existing ones. The key factor for the success of these campaigns is to detect potential churners before they leave the service and target them with such campaigns. Even when a customer has already decided to leave an MNO, it is very important to change their mind as fast as possible about leaving since it is known that when a customer leaves a service the probability that they will resume using it in the future becomes

[1]Correspondence to: Department of Network Engineering, Universitat Politècnica de Catalunya, Jordi Girona 1-3, Building C3, Office 308, 08034 Barcelona, Spain

lower with the pass of time.

The mainstream approach to churn prediction considers each customer individually. The influence of social factors in leaving an MNO, however, has not yet received significant consideration. Preliminary studies have shown, however, that members in the social circle of a subscriber also influence the subscriber to churn Dasgupta et al. (2008). It is natural to believe that when a person leaves a service, he also impacts the social circle around him with his actions. Social pressures to adopt new technology may also encourage users to move to an MNO that has the fastest data access or popular handsets. Thus, developing churn prediction systems that take social aspects into account poses an emerging theoretical challenge with potentially great practical implications.

The state of the art has focused on proposing methods to identify churners based on mining existing customer data that MNOs possess. However these techniques doesn't always offer clear explanations for churn reasons. This is the reason that, in this paper, we focus on a different technique called Agent-Based Modeling (ABM) which was used to model customer and market behavior in Twomey and Cadman (2002). We tried to capture the factors that can cause churn and created a model that is able to simulate churn in the mobile market in various scenarios where MNOs want to know the effects of, for example, implementing a new pricing approach, offering a new plan to customers, upgrading their network, etc.

We propose a model that includes some relevant demographic and psychographic characteristics and the utilization of usage profiles to describe customers individually. We chose these characteristics based on findings from research and white papers, reports and statistical data. This model also includes the interaction among customers. This interaction being the representation of social circles and the influence members of these social circles have between them. We use the work by Toivonen et al. (2006) to create a social graph that exhibits the features present in real life social networks. We propose a modification to this algorithm in order to take into account homophily, which is a principle that says that is more probable for people to associate with similar ones than with dissimilar people McPherson et al. (2001). This graph will represent the relations between customers and the similarity among customers will represent the strength of their relationship. The relations, their strengths and the information exchange among customers will then influence a customer behavior and the actions they make, apart from their characteristics.

In the experimentations carried out, we used data from EurostatEurostat to feed the model in the aim to offer realistic values that could characterize better customers, but other data sources could be used for the same task. We carried on experimentation on a hypothetical scenario to show how customers behave according to its environment and the social influence they are subject to. We compare the results of the proposed approach with the results when using the original algorithm by Toivonen et al. (2006) and when no social network exists.

We firmly believe the proposed approach is useful because MNOs can use it with the already available data they have of their customers, feed it to the model and utilize this model as a way to validate more realistically new approaches or strategies before implementation and have the certainty that results will not differ greatly from simulations. Another important feature of the proposed model is that it can be used to get insights on the customers according to their characteristics or sets of characteristics that can be later used in the decision making process to create personalized plans, marketing or sell strategies directed towards specific customers. We also proved that taking into account social aspects helps customers find their ideal services quicker. Furthermore, when using the proposed algorithm the grouping of friends is greater.

This paper is organized as follows: section 2 presents some basic concepts of homophily and social networks, and recent work on social churn identification. Section 3 explains the proposed approach. Details of the proposed approach implementation and experimentation are presented in sections 4 and 5, respectively. Finally, section 6 presents the conclusions and future work.

2. State of the art

2.1. Homophily

Homophily is the principle that is more probable for people to associate with similar ones than with dissimilar people McPherson et al. (2001). Homophily implies that distance in terms of social characteristics translates into network distance, the number of relationships through which a piece of information must travel to connect two individuals. It also implies that any social entity that depends to a substantial degree on networks for its transmission will tend to be localized in social space and will obey certain fundamental dynamics as it interacts with other social entities in an ecology of social forms. The presence of homophily has important implications on how information flows along the social network and, more generally, on how agents' characteristics impinge on social behavior.

Lazarsfeld and Merton (1954) distinguished two types of homophily: status homophily, in which similarity is based on informal, formal, or ascribed status, and value homophily, which is based on values, attitudes, and beliefs. Status homophily includes the major sociodemographic dimensions that stratify society—ascribed characteristics like race, ethnicity, sex, or age, and acquired characteristics like religion, education, occupation, or behavior patterns. Value homophily includes the wide variety of internal states presumed to shape our orientation toward future behavior.

2.2. Real life social networks

Some of the general features of social networks are:

1. Low tie density: The cognitive ability of human places an upper bound on the number of ties one may maintain Dunbar (1992). On the other hand, other factors corresponding to baseline homophily can also play a role Feld (1981).
2. Short average geodesic distances: Geodesic distance between two actors is defined to be the length of the shortest connection between them. In large social networks, it is believed that the typical geodesic distance between any two actors remains small. This property was demonstrated empirically by Milgram (1967) in his classical experiment, contributing to the popular saying that no one on this earth is separated from you by more than six "handshakes".
3. High level of clustering: Clustering is defined to be the average probability that two friends of an actor are themselves friends. Equivalently, it is a measure of how having a mutual friend will heighten the conditional probability that the two friends of an actor will be friends themselves. In their well-known article, Watts and Strogatz (1998) demonstrated the importance of short-cuts in social networks that simultaneously display high clustering and short average geodesic distances. Such an idea of short-cuts dates back to Granovetter (1973) arguments on the strength of weak ties .
4. Positively skewed actor degree distribution: The degree of an actor is the number of social ties he/she has. In many social networks, a majority of actors have relatively small degrees, while a small number of actors may have very large degrees. This feature is displayed in a wide range of social networks. While it is still debated whether generic social networks have power law, exponential, or other degree distributions, or indeed whether there is any generic distribution at all Jones and Handcock (2003), there is no doubt that degree distributions are in general positively skewed.
5. Existence of communities: In many cases, clustering does not occur evenly over the entire network. We can often observe subgroups of actors who are highly connected within themselves but loosely connected to other subgroups which are themselves highly interconnected. We call these highly connected subgroups communities Newman (2004). A long tradition in social network analysis has developed a range of algorithms to identify these cohesive subsets of nodes Wasserman and Faust (1994).

2.3. Social network models

Boguna et al. (2003) proposed a model of social network formation that parameterizes the tendency to establish acquaintances by the relative distance in a representative social space. Link nodes with prob. $p = \frac{1}{\left(1+\left(\frac{d}{b}\right)^{\alpha}\right)}$, where d is their distance in the social space. (h_{max} can be absorbed within b). If treated many-dimensionally, similarity along one of the social dimensions is sufficient for the nodes to be seen as similar.

Vázquez (2003) analyzed a model for social network evolution based on the existence of potential connections between the neighbors of a vertex. The mechanism is the following: (1) With probability $1-u$, add a new node to the network, connecting it to a random node i. Potential edges are created between the newcomer n and the neighbors j of i (a potential edge means that n and j have a common neighbor, i, but no direct link between them). (2) With probability u, convert one of such potential edges generated on any previous time step to an edge. Potential edges generated by converting an edge are ignored.

Wong et al. (2006) distribute N nodes according to a homogeneous Poisson point process in a n-dimensional social space of unit area. They create a link between each node pair separated by distance d with probability $p + p_b$ if $d < H$, and with probability $p{-}p$ if $d > H$ (where $p_{\triangle}(p, p_b, H)$ is such that the total fraction p of all possible links is generated).

Toivonen et al. (2006) developed a model which produces very efficiently networks resembling real social networks in that they have assortative degree correlations, high clustering, short average path lengths, broad degree distributions and prominent community structure. The model is based on network growth by two processes: attachment to random nodes and attachment to their neighborhood.

Goodreau et al. (2009) used demographic measures on individuals (age, sex, and race) and network measures for structural processes operating on individual, dyadic, and triadic levels. They model friendship formation as a selection process constrained by individuals' sociality (propensity to make friends), selective mixing in dyads (friendships within race, grade, or sex categories are differentially likely relative to cross-category friendships), and closure in triads (a friend's friends are more likely to become friends), given local population composition.

Currarini and Vega-Redondo (2013) approach hinges upon two key assumptions: (i) the establishment of ties with individuals that differ in some relevant characteristics (e.g. race or language) implies a costly investment; (ii) the search for suitable ties is more effective in larger pools. Under these assumptions, the induced game was shown to have a threshold equilibrium where groups outbreed if, and only if, their size falls a certain level. This simple structure of the equilibrium has implications that match the empirical evidence found in both friendship and marriage data. Specifically, it is consistent with the regularities observed on the pattern of in-group and cross-group ties, as well as with the non monotonicity displayed by the Coleman homophily index.

2.4. Social churning prediction

Phadke et al. (2013) developed a churn prediction algorithm based on a social network analysis of a mobile call graph. They provided a formulation that quantifies the strength of social ties between users based on multiple attributes and then applied an influence diffusion model over the call graph to determine the net accumulated influence from churners. It was demonstrated that by combining this influence and other social factors with more traditional metrics and by applying machine-learning methods to compute the propensity to churn for individual users, the accuracy of these methods was improved.

Motahari et al. (2014) proposed a method to identify "churn influencers" whose influence makes their social contacts churn subsequently. To build their model, they scored the subscribers' influence level in a way that can take current churn models into account. They used large scale call records to identify social network and communication features that abstract the strong influencers.

Han and Ferreira (2014) looked at the effect of peer influence on churn and tried to disentangle it from other effects that drive simultaneous churn across friends but that do not relate to peer influence. Empirical analysis was performed on a large dataset of call detail records from a major European wireless carrier over a period of 10 months. Survival models and generalized propensity score were applied to identify the role of peer influence. It was shown that the propensity to churn increases when friends do and that it increases more when many strong friends churn, a result suggesting that churn managers should prevent group churn instead of looking at churn on an individual basis. It was also shown that survival models fail to disentangle homophily from peer influence overestimating the effect of peer influence.

Deri and Moura (2014) first developed a graph representation of the dataset where nodes represent callers and edges connect callers who call each other. Secondly, they associated every caller in the network with an activity vector, that collects several usage statistics between a caller and its neighbors, and a subgraph of M neighbor callers which they call affinity graph. They use activity levels computed from subgraphs of the affinity graph as features to classify callers. Their anomaly classifier is a cascaded classifier with stages that combine naive Bayes and decision tree classifiers.

In Abd-Allah et al. (2014), they constructed an undirected call graph and evaluated the social tie strength using new interactional attributes, derived from basic call attributes, to ensure the validity of the calculated tie strength. They proposed an influence propagation model, where the strongest ties are exploited for churn influence transfers from one node to another.

To infer potential users to join target services from the competitors in the near future, Hsu et al. (2014) proposed a framework including feature extraction, feature selection, and classifier learning to solve the problem. First, they construct a heterogeneous information network from the call detail records of users. Then, they extract the explicit features from potential users' interaction behavior in the heterogeneous information network. Moreover, they extract community-based implicit features of potential users. After feature extraction, they explore the Information Gain to select the effective features. They use the effective explicit and implicit features to learn potential user classifiers, and use the classifiers to determine the potential users.

Richter et al. (2010) proposed Group-First Churn Prediction. Their method works by identifying closely-knit groups of subscribers using second order social metrics derived from information theoretic principles. The interactions within each group are then analyzed to identify social leaders. Based on Key Performance Indicators that are derived from these groups, a novel statistical model is used to predict the churn of the groups and their members.

Dasgupta et al. (2008) proposed a spreading activation-based technique that predicts potential churners by examining the current set of churners and their underlying social network. They obtained the call graph from Call Detail Record data. Relationships between people are based on the duration of voice calls, call frequency etc. that are exchanged during a certain period. They found that using this spreading activation-based technique performs better than using a decision-tree technique to predict churners. They also found that using connectivity and interconnectivity attributes to improves the performance of the decision-tree technique.

3. Proposed approach

A customer is defined by its profile or characteristics and its behavior, both personal and social. In the following subsections these aspects will be detailed.

3.1. Customer profile

A user profile is formed by a set of attributes, which can take different values. Then, a user profile is a set of attributes with specific given values. A customer is defined by a set of demographic and psychographic characteristics, where some are independent and others depend on the value of other characteristics. Figure 1 shows these characteristics and their relations or dependencies. As in Hassouna and Arzoky (2011), we explicitly chose gender and age because they appear consistently as variables in the state of art.

Budget was also chosen because it's a restrictive variable when buying any service or product, which for this work is of great importance because we are trying to model purchase and post-purchase behavior. From EurostatEurostat data we found that on average, income varies 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 age, gender and budget are related. Assimakopoulos (2013) segmented mobile Internet customers into classes based on demographic characteristics, payment models and attitudinal characteristics.

Across segments it could be seen that mobile services expenditures were linked to age. This was found in Ernst & Young Global Limited (2013), too.

Age is a widely used demographic variable to characterize the adoption of technologies between two or more consumer groups, like in Morris and Venkatesh (2000); Pagani (2004); Papaioannou et al. (2011). In this work we deem this affinity for technology as tech savviness. Sell et al. (2014) found that different attitudes towards technology define behavior regarding use of mobile applications. Im et al. (2011) obtained similar results with other types of technologies. Quorus Consulting Group (2012); Ernst & Young Global Limited (2013) showed mobile device and mobile services usage varies among different age groups. This led us to relate tech savviness to customer profiles.

Brand loyalty is defined as consumer's preference for a particular brand and a commitment to repeatedly purchase that brand. MNOs seek to become the objects of loyalty in order to retain customers. Kumar and Lim (2008) found that age has an apparent effect on mobile service perceptions and loyalty decisions. This is why we include this characteristic and relate it to age.

We propose the utilization of usage profiles, which we define according to the type of applications customers use as showed in table 1. Different applications demand different QoS and also, on average, generate different amounts of traffic. The amount of data and QoS sensitivity have and impact on purchase and post-purchase behavior. Findings in Kumar and Helmy (2010); Papaioannou et al. (2011); Peslak et al. (2011); Shi et al. (2010) showed that genders have different affinities for different types of applications. Rocha et al. (2012) showed that customer profiling can be of crucial importance to several networking tasks, such as resources management, services personalization and security. In fact, by describing a customer profile in terms of the web-applications that are used, one can easily and timely infer the bandwidth requirements.

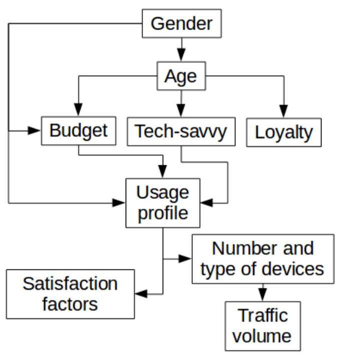


Figure 1: Customer characteristics and their relation

	Application 1	…	Application n
Profile 1	Mean data events per period	…	Mean data events per period
⋮	⋮	⋱	⋮
Profile n	Mean data events per period	…	Mean data events per period

Table 1: Usage profiles and applications

3.2. Social network

As already mentioned, it has been shown in preliminary studies, like the one by Dasgupta et al. (2008), that members in the social circle of a customer also influence the customer to churn. It is natural to believe that when a person leaves a service, he also impacts the social circle around him with his actions. With this in mind, we decided it was important the proposed model took into account social behavior.

3.2.1. Network creation

For us, it was very important that the social network resembled those in real life. So, we looked for a model that produced a social network close to reality. In this quest, we came across the work by Toivonen et al. (2009), which reviewed, classified and compared recent models for social networks that have mainly been published within the physics-oriented complex networks literature. The models fall into two categories: those in which the addition of new links is dependent on the (typically local) network structure (network evolution models, NEMs), like the works of Toivonen et al. (2006) and Vázquez (2003), and those in which links are generated based only on nodal attributes (nodal attribute models, NAMs), like the works of Boguna et al. (2003) and Wong et al. (2006). They fitted models from each of these categories to two empirical acquaintance networks with respect to basic network properties. Then, they compared higher order structures in the resulting networks with those in the data, with the aim of determining which models produce the most realistic network structure with respect to degree distributions, assortativity, clustering spectra, geodesic path distributions, and community structure (subgroups with dense internal connections). It was found that the NAMs successfully produce assortative networks and very clear community structure. However, they generate unrealistic clustering spectra and peaked degree distributions that do not match empirical data on large social networks. On the other hand, many of the NEMs produce degree distributions and clustering spectra that agree more closely with data. They also generate assortative networks and community structure, although often not to the same extent as in the data. Furthermore, among the reviewed NEMs, the one proposed by Toivonen et al. (2006) performed better when compared to the data.

It is because of these reasons that we decided to use the work by Toivonen et al. (2006) to create a social network graph structure resembling real social networks in that they have assortative degree correlations, high clustering, short average path lengths, broad degree distributions and prominent community structure. The model is based on network growth by two processes: attachment to random nodes and attachment to their neighborhood. However, these growth processes don't take into account nodal attributes, encoded in the user profile, to create connections between them, and hence represent social ties between nodes. We propose to extend the work by Toivonen et al. (2006) and follow the principle of homophily which says that is more probable for people to associate with similar ones than with dissimilar people. We decided that it was important that homophily was taken into account in the creation of the social network because, as already stated, it has important implications on how information flows along the social network and includes the wide variety of internal states presumed to shape our orientation toward future behavior.

We decided to measure homophily as the euclidean distance between two nodes according to their attributes. Each attribute would be measured in a different dimension and so the resultant distance between two nodes would be the euclidean distance in a n-dimensional space, being n the number of attributes a node has.

$$distance_{pq} = \sqrt{w_1\left(p_1 - q_1\right)^2 + w_2\left(p_2 - q_2\right)^2 + \ldots} + w_n\left(p_n - q_n\right)^2$$

where p, q are nodes, $1, 2, \ldots, n$ are the number of attributes and w is a weight given to a dimension. w can be used to normalize attributes or give more or less importance to a given attribute. In this work, the maximum distance value is 1.

The algorithm proposed by Toivonen et al. (2006) with our proposed extension is as follows:

1. Obtain affinity matrix.
2. Start with a seed network of N_0 nodes with the highest affinity according to the affinity matrix.
3. Pick on average $m_r \geq 1$ random nodes as initial contacts.
4. Pick on average $m_s \geq 0$ neighbors of each initial contact as secondary contacts.
5. Chose the node with the smallest distance to the selected initial and secondary contacts.
6. Connect the new vertex to the initial and secondary contacts.
7. Repeat steps 3–6 until the network has grown to desired size.

3.2.2. Influence over friends

Although people can have a number of friends, not all of them share the same bond as the others. It varies on different factors, but in this work we decided to use the converse value of the distance between two customers. Meaning that more similar customers share a stronger bond. As the minimum value of distance is 0, meaning that both customers have the exact same profile. The influence between two customers with the exact same profile would be 1, which is the maximum value of influence.

3.3. Behavior

In this model we follow the buying decision process introduced in Dewey (2007). This process consists of five stages:

1. Problem/need recognition. In this stage the customer is not subscribed to a data plan or is not satisfied with his current service plan or MNO.
2. Information search. The customer first has to know which MNOs exist in the market and the current plans they are offering. In this work, this will decided by a parameter indicating the MNOs' market aggressiveness. In case that a customer is thinking of changing plan to an MNO and he is satisfied with the MNO but unsatisfied with his current service plan, only plans from these MNO will be taken into account. If there are no more suitable service plans from the same MNO, service plans from other MNOs will also be taken into account. Also, customers ask their friends for their current subscriptions and their evaluations.
3. Evaluation of alternatives. Customers will evaluate service plans according to some criteria dictated by their characteristics and current state, and discriminate the ones that doesn't meet these criteria. In this work, new customers will discriminate plans based on their cost. Customers that are thinking of changing from their current plan to a new one, will discriminate plans based first on the price and then based on the reason that made them look for other alternatives, such as price, insufficient data or bad QoS. Plans which a customer has previously been subscribed to and have not varied overtime, won't be taken into account to avoid going back and forth between plans.
4. Purchase decision. Users will decide based on the information shared by their friends. However, friends' evaluations will not be processed by the customer as it is. The influence each friend has will also come into the equation. So, customers will have to take into account the actual evaluation and the influence of each of their friends.
5. Post-purchase behavior. In this stage, customers will evaluate the service plan they are subscribed to and the MNO that is providing the service. These evaluations will drive the customer to keep the current service plan, look for different service plan options within the same MNO or churn. Figure 2 shows the post-purchase behavior customers exhibit in this work. Customers will evaluate service plans based on price, plan's data cap and the perceived QoS. Customers will also evaluate the MNO they are subscribed to based on the Customer Experience (CE) model proposed in Anaman and Lycett (2010). This model assigns weights to different factor categories to denote their importance to customers. The CE model is represented by a utility function that is a sum of the product of each category multiplied by its weight. The score scale is shown on a 0 to 100 point scale,

and the higher the score, the more satisfied the customer. A summary of the CE model is shown in table 2. Once customers have evaluated their service plans and MNOs, they will share their MNOs evaluations according to the CE model with their friends. Once again, customers will take into account their friends' evaluations of MNOs to see if there is a better MNO out there or the current MNO is the better option.

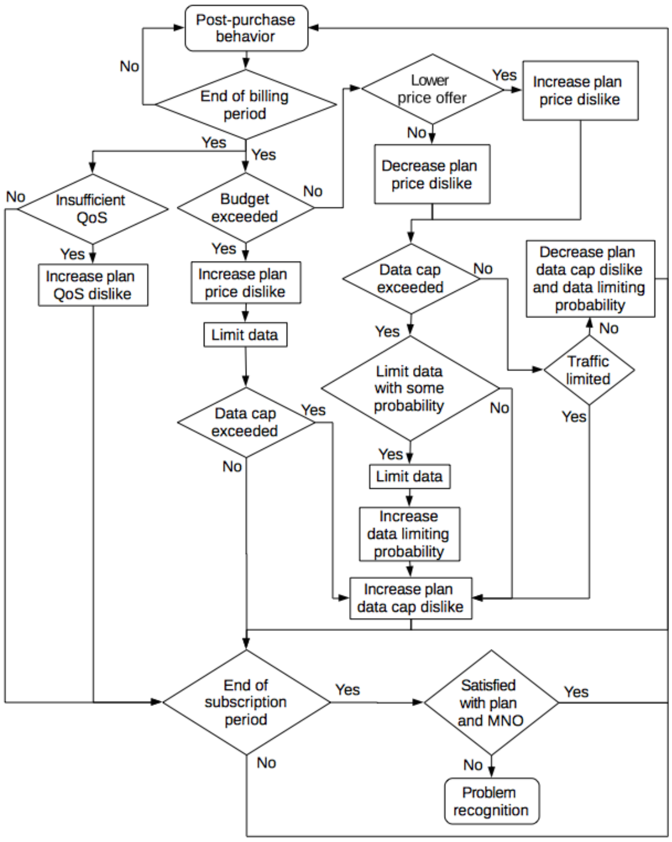


Figure 2: Post-purchase behavior

Category	Weighting	Description
Cost	18.18	Cost competitiveness and plan usage
Handset	9.09	Handset repairs and known issues
Coverage	23.38	QoS and coverage
Customer services	18.18	Complaint volume and repetition
Offerings and promotions	18.18	Savings from offerings and promotions
Billing	12.99	Billing complaints

Table 2: Customer Experience model proposed by Anaman and Lycett (2010)

4. Implementation

The model's parameters are distributions or scalar values that describe both the customers and MNOs characteristics. In the simulation initialization, characteristics for customers are assigned according to the distributions used as parameters. MNOs characteristics are assigned as well.

Initially customers are not subscribed to any MNO, however they can also be assigned to an MNO according to the MNO market share. Customers start interacting with the MNOs, once the simulation starts, according to the buying decision process.

For this specific implementation each simulation time unit represents a second, although the end user would only specify the number of days for the simulation. This is in order to simulate congestion conditions that may arise taking into account the different usage profiles and applications. There are two ways of defining QoS: (1) as parameter or (2) as a function of the resources MNOs have and the traffic generated by the customers. MNOs' behavior can be implemented according to different pricing, marketing, QoS assurance approaches, or any other techniques or approaches from the state of the art. This is not the focus of this work.

OMNeT++OpenSim Ltd. was chosen as the framework for implementation of the proposed approach. It provides infrastructure and tools for writing discrete event simulations. It has 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.

Three modules were created as depicted in figure 3. A module to create the social network using the proposed algorithm as explained in section 3.2 was created. The tool selected to handle and perform all network operations was The Stanford Network Analysis Platform (SNAP). SNAP is a general purpose network analysis and graph mining library. It is written in C++ and easily scales to massive networks with hundreds of millions of nodes, and billions of edges. It efficiently manipulates large graphs, calculates structural properties, generates regular and random graphs, and supports attributes on nodes and edges. Gender, age, budget, tech savviness, mean traffic volume where chosen as the characteristics to calculate the measure of homophily. In order to include the usage profiles as a dimension in the homophily space, the importance that usage profiles give to QoS, and the rate at which usage profiles increment their dislike towards a plan depending on billing, QoS and data cap, were used. The minimum and maximum values of each dimension were used to normalize each dimension. Initially all users are created individually and then they send their profiles to the network generator. The network generator calculates the social distances and influences and then uses the proposed network generation algorithm the create the social network. Once the social network is created, customers are informed of their social circles and the influence among friends. This exchange of information is done through messages as seen in figure 3.

The customer model described in section 3 was implemented as a simple module encapsulating the process of assigning customers characteristics and customer behavior. This model includes the probability that customers complain when an incident happens regarding billing or QoS, which are defined as parameters. For the purpose of simplicity, customers perceive QoS as the average bandwidth available to them. In this work, QoS has to do with the conditions of the network and by that we mean the amount of bandwidth resources an MNO has, the number of subscribed customers, the amount of traffic they impose on the network and the time at which they do it.

The MNO module represents the characteristics of an MNO such as the pricing scheme, the amount of resources, the offered service plans and other characteristics such as customer service and marketing parameters. A set of plans are defined by parameters price, overage charges and data cap. General parameters of the MNO include the available bandwidth, cost competitiveness and plan usage, handset repairs and known issues, and savings from offerings and promotions. The probability of resolving complaints is also a parameter.

Both modules, MNO and customer, exchange information through messages as shown in figure 3, such as customer subscription or unsubscription, service payment, complaints, etc. An example of this information exchange is when customer sends a complaint to the MNO and then the MNO answers with a positive or negative resolution. Additionally, customers communicate among themselves sharing their MNO's evaluations to their social circles.

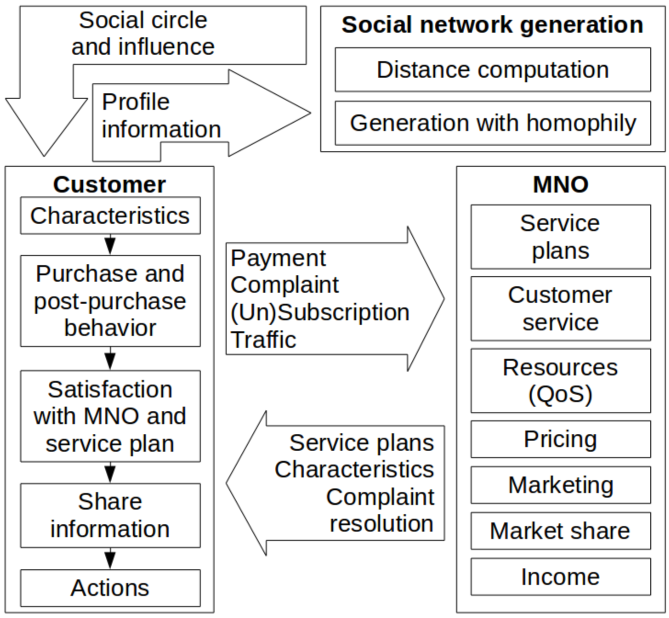


Figure 3: General model

5. Evaluation

In order to evaluate the proposed model a hypothetical scenario was devised. Two thousand customers are interacting with two MNOs, MNO 1 and MNO 2. This scenario is depicted in figure 4. Both MNOs have equivalent characteristics such as marketing aggressiveness index, customer service level, billing complaints index, handset availability index. All of these are set to 90%, except for billing complaints index that is set to 10%. Available resources to provide service to customers are also initially equivalent in both MNOs and this value is set to 608 kb/s. Each MNO offers one plan with equivalent characteristics: same data cap (2 GB), price (10 currency units), overage charges (5 currency units per GB), billing and subscription time (30 days). At some point of the simulation, MNO 2 would increment the available bandwidth it has to provide service to customers to 768 kb/s.

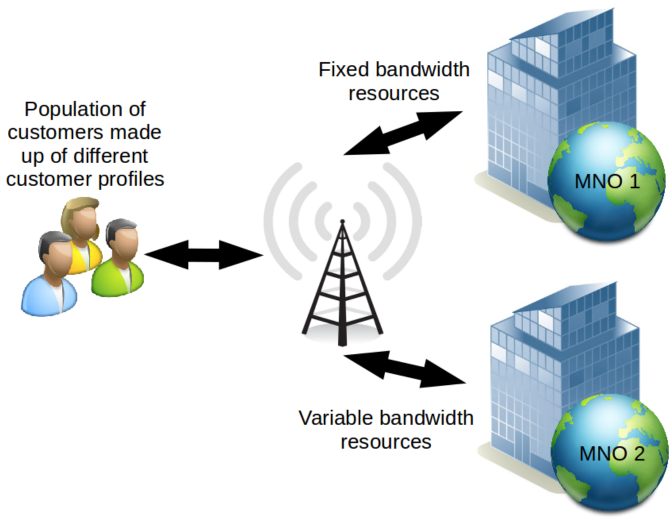


Figure 4: Simulation scenario

For these experiments the total simulation time is 1440 days, being at day 720 when the change in available bandwidth happens.

Table 3 shows the general parameters for the experiment. MNO related parameters can be seen in table 4a and table 4b shows the parameters of the offered plan for both MNOs.

Data from EurostatEurostat, whenever possible, was used as input for the customer module. For other characteristics and parameters where data from EurostatEurostat could not be used as input, distributions and values we deemed appropriate according to findings

Simulation time	1440 days
Resources change time	720 days
Number of customers	2000
Number MNOs	2

Table 3: General parameters

Minimum bandwidth	384 kb/s
Maximum bandwidth	768 kb/s
Increment/decrement bandwidth step	16 kb/s
Marketing aggressiveness index	90%
Customer service level	90%
Billing complaints index	10%
Handset availability index	90%

(a) General

Data cap	2 GB
Price	10 currency units
Overage charges	5 currency units per GB
Billing time	30 days
Subscription time	30 days

(b) Offered plan

Table 4: MNO Parameters

already mentioned in subsection 3.1 where used instead. EurostatEurostat data from 2014 was used for: sex, age and income distribution. For loyalty a function that increments with age was used. For tech savviness a function that decreases with age was used. Females were given a higher probability to be socials, and a lower probability to be gamers. Males were given a higher probability to be gamers, and a lower probability to be socials. Tech savvy customers were given a higher probability to be gamers. No tech savvy customer were given a higher probability to be moderate. Moderate, music and social customer were given a higher probability to have a smartphone. Gamers and video customers were given a higher probability of having a tablet. Workers were given a higher probability to having a mobile computer.

Distributions, probabilities and functions to assign customers characteristics, as already explained in subsection 3.1, will now be mentioned. 2014 data from EurostatEurostat was used to create the following distributions and functions. Discrete distributions for gender share and age distribution according to gender. The gamma-gompertz function, reported in Bemmaor and Glady (2012) was chosen as wealth distribution because it was the distribution that better fitted maximum monthly income percentiles data. Parameters for this function are shown in table 5a. The function $meanbudget(age) = a * exp(b * age) + c * exp(d * age)$ was obtained from data regarding mean income for age intervals according to sex. Parameters for this function can be seen in table 5b. Data for computer and Internet usage in different age intervals was used to obtain the function $probabilityTechSavvy = (p1 * age * age + p2 * age + p3)/(age + q1)$. Table 5c shows the values for these parameters.

s	0.2782
b	24.56
β	52.72

(a) Wealth distribution

	Males	Females
a	-0.2411	-0.9996
b	0.07355	0.06179
c	61.79	56.94
d	0.01057	0.01395

(b) Mean budget function

$p1$	-0.02287
$p2$	2.061
$p3$	6.4x10^{-3}
$q1$	14.88

(c) Tech savvy probability

age_{min}	14
age_{max}	74
$loyalty_{min}$	0.8
$loyalty_{max}$	0.2

(d) Loyalty

Table 5: Customer profiles parameters

The loyalty index or level function is the following: $loyalty\,(age) = \frac{(age-age_{min})(loyalty_{max}-loyalty_{min})}{(age_{max}-age_{min})} + loyalty_{min}$. The values of these parameters are shown in table 5d. This function was used following the findings in Kumar and Lim (2008). Probabilities for usage profiles according to genders and tech savviness are shown in table 6.

Six usage profiles are taken into account in this implementation as shown in table 8: moderate use customers, customers that play online games, customers that use the service for work related activities, customers that are very active in social networks, customers who mainly listen to music and customers who mainly watch videos. For each one of them we assigned different QoS importance levels. The share of each usage profile in the population and the importance each usage profile gives to QoS are shown in table 7. Also different dissatisfaction levels to service plan evaluating factors are assigned to each usage profile. This dissatisfaction levels, shown in table 9, define how fast customers with different usage profiles start considering changing their current plan. Each period, in this case a month, customers evaluate their plans summing these dissatisfaction levels for each factor they are not satisfied with. When customers reach a dissatisfaction level of 100, they will start looking for other plans. As already mentioned customers can have more than one type of mobile device. Devices probabilities for each usage profile are shown in table 10. Each event data amount according to application and device are shown in table 11. This table was made with data from MNOs websites from different countries EE; O2; Vodafone.

For the network generator, the same parameters used in the work by Toivonen et al. (2006) were used. The initial network size was set to 10% the number of customers in the experiments and is generated by adding pairs of nodes with the lowest distance. The probability to define the number of initial connections was set to 0.95 for 1 initial

	Moderate	Gamer	Social	Music	Worker	Video
Female	0.16	0.08	0.25	0.16	0.16	0.16
Male	0.16	0.25	0.08	0.16	0.16	0.16
Tech savvy	0.07	0.21	0.21	0.21	0.14	0.14
No tech savvy	0.30	0.10	0.10	0.10	0.20	0.20

Table 6: Usage profile probabilities for sex and tech savviness

	Share	QoS importance
Moderate	26%	70%
Gamer	34%	95%
Social	21%	80%
Music	8%	90%
Worker	7%	95%
Video	4%	90%

Table 7: Usage profile share and QoS importance

contact and 0.05 for 2 initial contacts. The number of secondary connections is selected from $U[0,3]$. In order to differentiate profiles more clearly, the distances between profiles were normalized using the maximum and minimum values found in the experiment. 0.1 and 0.9 are used as the minimum and maximum distances when normalizing but if lower or higher values are found in the experiment, these are used instead.

5.1. Percentage of friend circle on same MNO

We decided this was a very representative way of showing the benefits of taking into account homophily in the process of the social network generation. Customers with similar profiles should behave similarly and make similar decisions. This would have the effect of a majority of customers in a social circle being subscribed to the same MNO. Also, due to customers having social ties with other customers with predominantly higher influence from those with similar behavior, the shared experience in the social group will help customers find their "ideal" MNO and service plan quicker according to their profile.

The percentage of friends subscribed to the same MNO is obtained counting individually the number of friends subscribed to the same MNO divided by the number of friends subscribed to any MNO, the same or other.

Figures 5, 6, 7, 8, 9 and 10 show the customers' friend circle percentage subscribed to the same MNO for the usage profiles. In these figures the original algorithm by Toivonen et al. (2006) and the proposed social network generator are compared. The experiment with no social network is not accounted because there would be no way of obtaining the social circle percentage that is subscribed to the same MNO. Each figure shows the percentage for MNO 1 and MNO 2 for each usage profiles. It can be seen that for the case of MNO 2 the average social circle percentage subscribed to the same MNO for profiles with a higher sensitivity to QoS, according to table 7, is higher than that obtained with the original algorithm. Specially after the increment in the available bandwidth, which means that friends with a higher sensitivity to QoS group in the MNO offering the higher bandwidth. In the same way, customers subscribed to MNO 1 with profiles with lower sensitivity to QoS have an average social circle percentage subscribed to the same MNO higher than that obtained with the random social network generator. This means that friends with a lower sensitivity to QoS group in the MNO offering the lowest bandwidth.

5.2. Churn and subscriptions

Figures 11, 12, 13, 14, 15 and 16 show the amount of churn and number of subscriptions MNO 1 and 2 present, respectively. It can be seen that for both cases where there exists a social network values for both churn and subscriptions are similar. However it can be noted that when a social network is present, both indicators get more quickly to their final values than in the case where there is not a social network. This can be attributed to the information that is shared between similar customers that get to their "ideal" option faster than in the case where there is not information sharing.

5.3. Social network graph

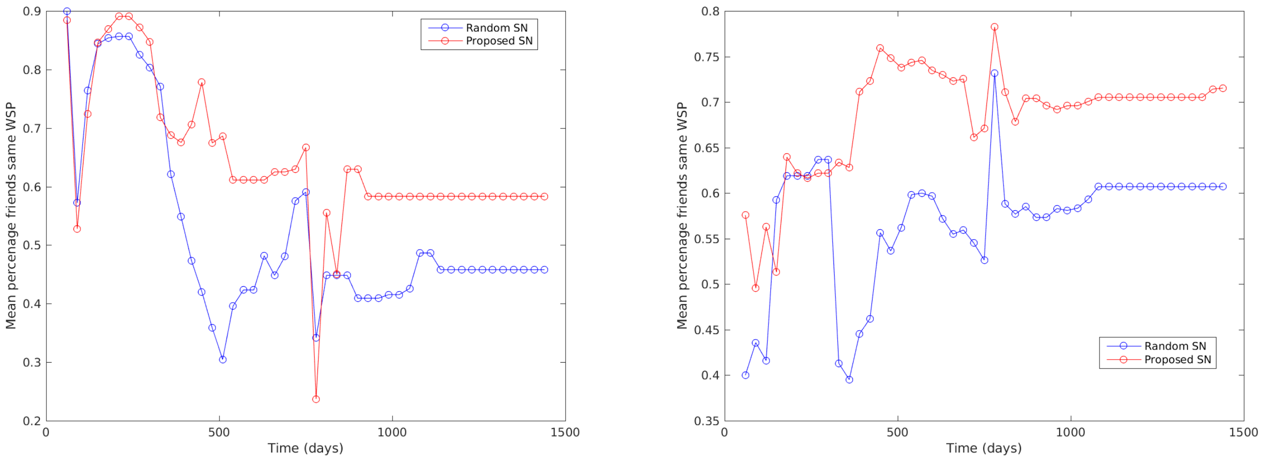
Figures 18 and 19 show the biggest components of the social network graph obtained with the original algorithm and with the proposed algorithm, respectively.

Each node represents a customer and each edge represents a bidirectional social tie. Nodes are colored according to their usage profile. Blue nodes represent moderate customers, green nodes represent gamer customers, cyan nodes represent online social customer, pink nodes represent music customers, red nodes represent worker customers, and yellow nodes represent movie customers.

Comparing both figures, it can be seen that we accomplished our goal by adding the homophily measure into the algorithm proposed by Toivonen et al. (2006), which was that it was more probable that customers with similar profiles would have social ties. In this case, represented by the usage profiles with different colors. This is also proven using a measure of heterogeneity proposed in Harris and Udry (2015). This measure assesses the heterogeneity of a customers network with respect to the value of an attribute. The formula used to calculate customer-network heterogeneity with respect to attribute A is:

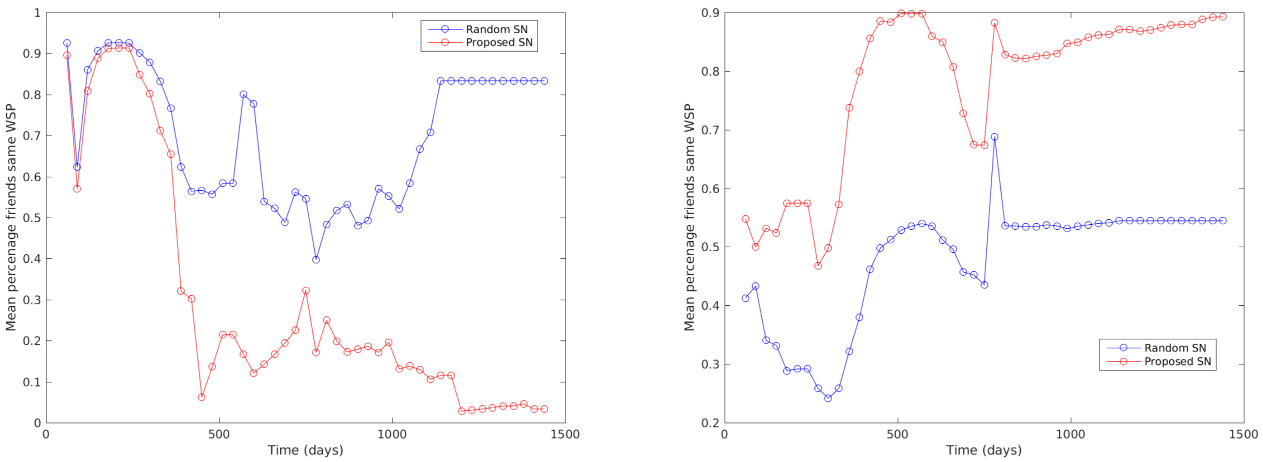
	Moderate	Gamer	Social	Music	Worker	Video
Email	30	150	150	150	2400	150
Music stream (min)	0	0	240	1200	0	240
Music download (song)	5	20	30	180	10	30
Video stream (min)	12	120	120	600	0	1800
Video call (mins)	0	0	20	0	240	0
Audio call (mins)	0	0	120	0	480	0
Surf web (pages)	150	500	1500	600	600	600
Social 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

Table 8: Applications and usage profiles



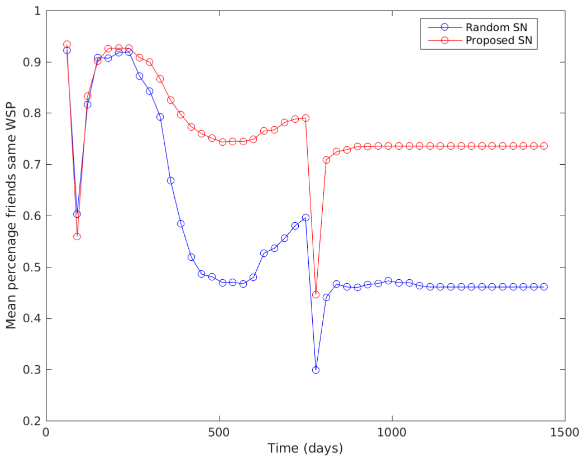
(a) MNO 1 (b) MNO 2

Figure 5: Percentage friend circle for music customer

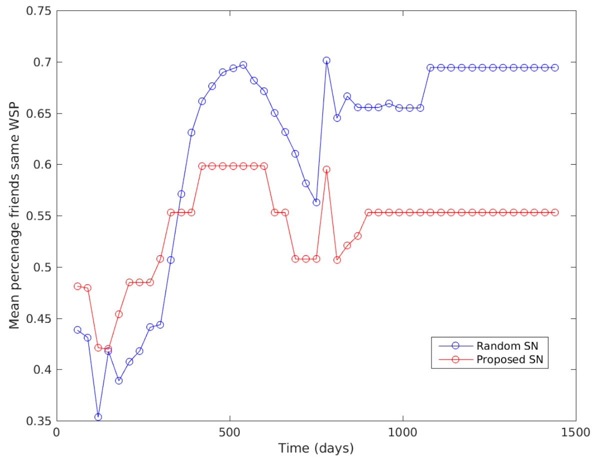


(a) MNO 1 (b) MNO 2

Figure 6: Percentage friend circle for gamer customer

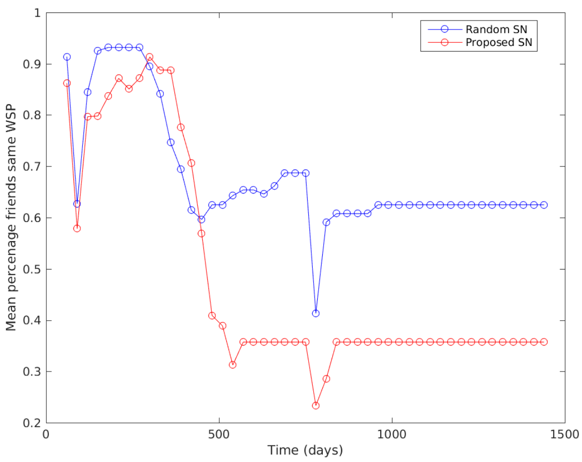


(a) MNO 1

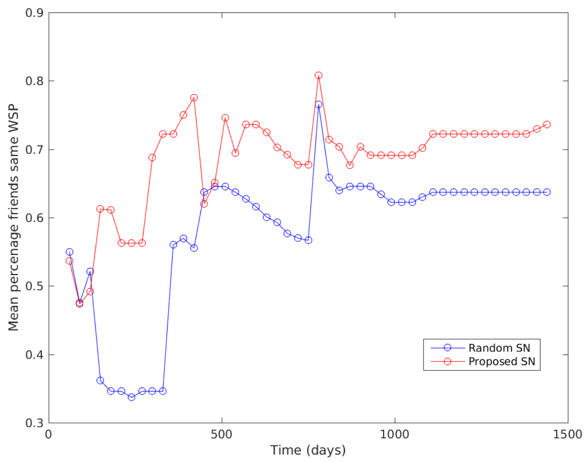


(b) MNO 2

Figure 7: Percentage friend circle for moderate customer

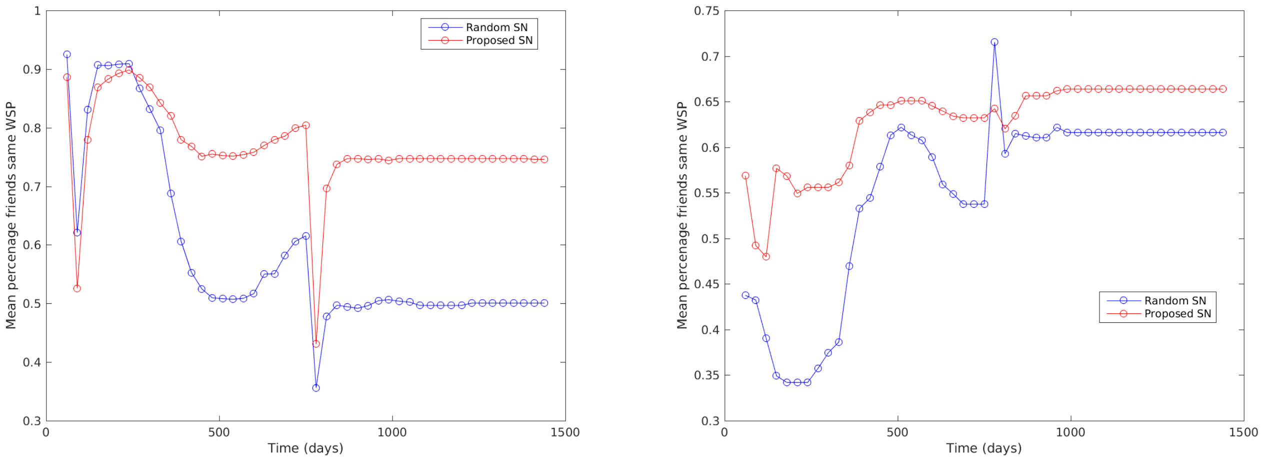


(a) MNO 1



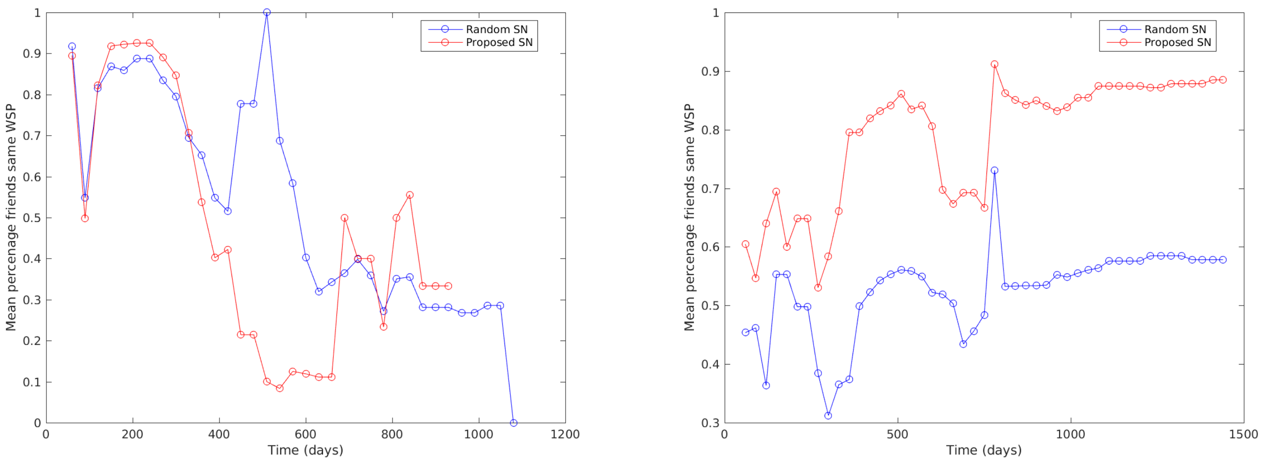
(b) MNO 2

Figure 8: Percentage friend circle for video customer



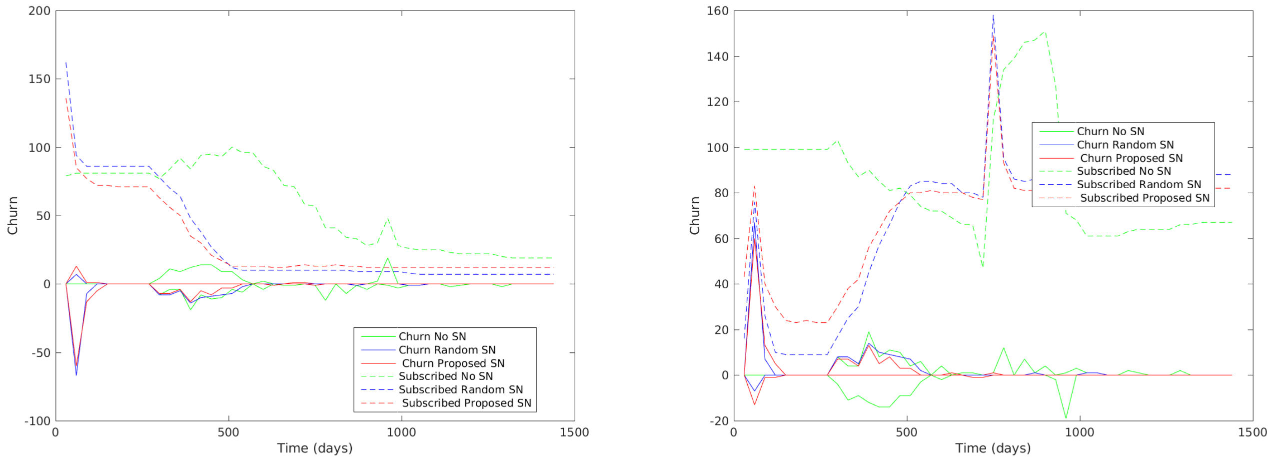
(a) MNO 1 (b) MNO 2

Figure 9: Percentage friend circle for social customer



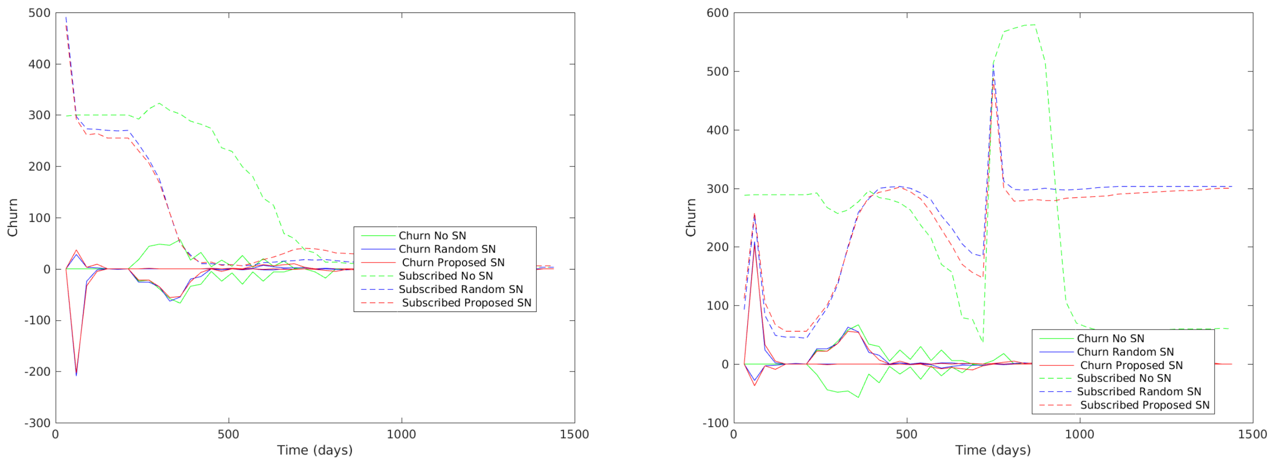
(a) MNO 1 (b) MNO 2

Figure 10: Percentage friend circle for work customer



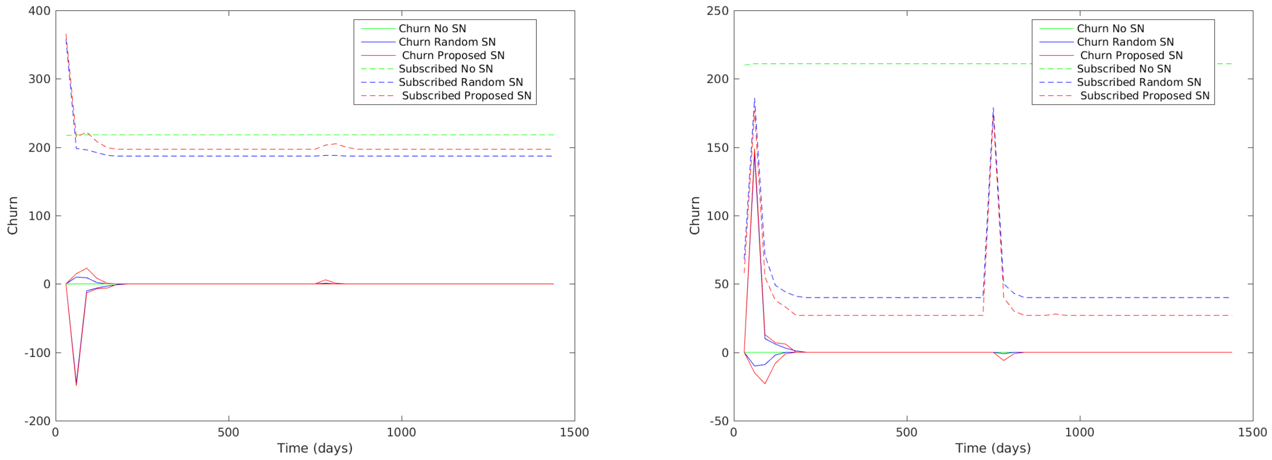
(a) MNO 1 (b) MNO 2

Figure 11: Music customers churn and subscriptions



(a) MNO 1 (b) MNO 2

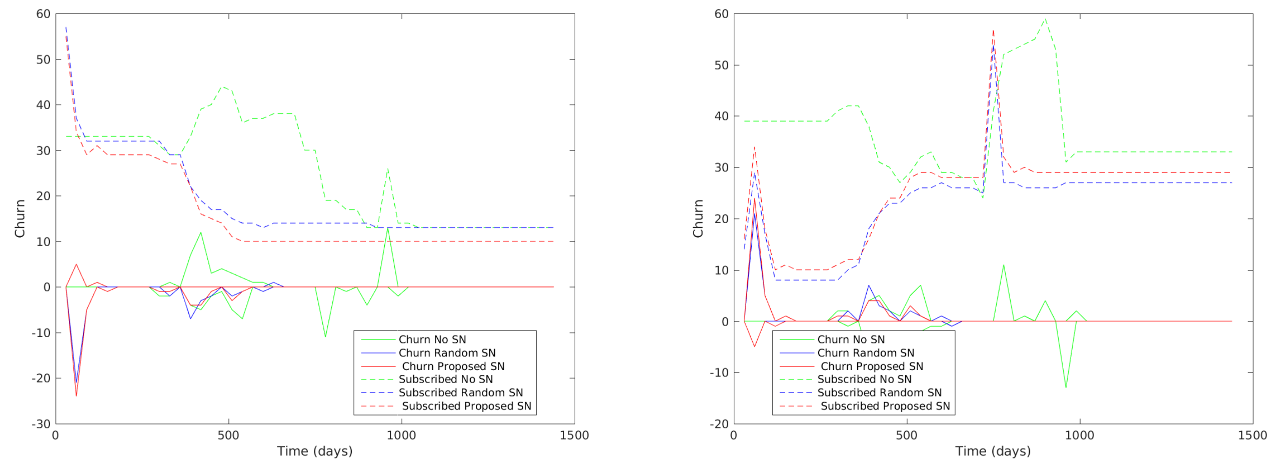
Figure 12: Gamer customers churn and subscriptions



(a) MNO 1

(b) MNO 2

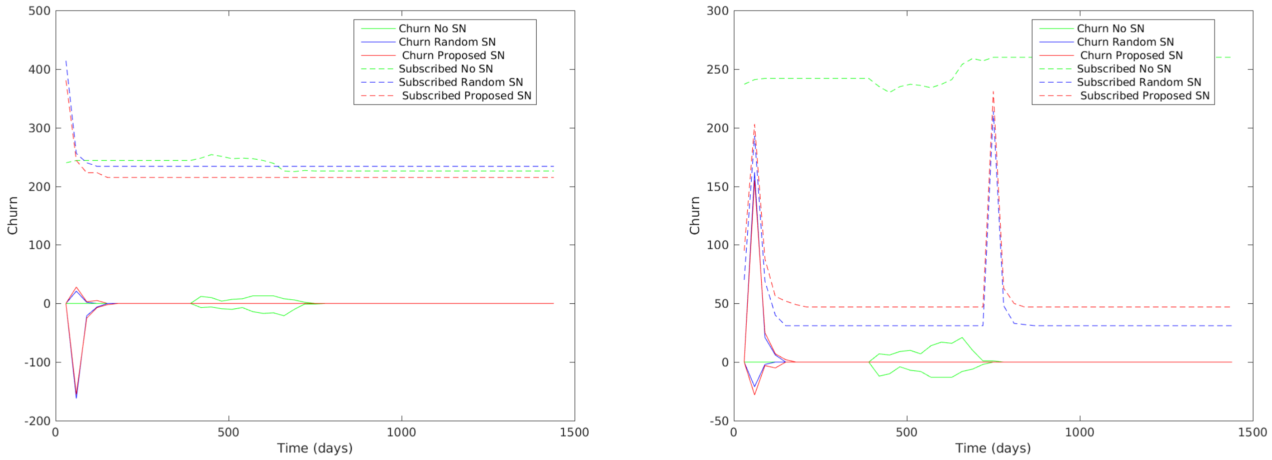
Figure 13: Moderate customers churn and subscriptions



(a) MNO 1

(b) MNO 2

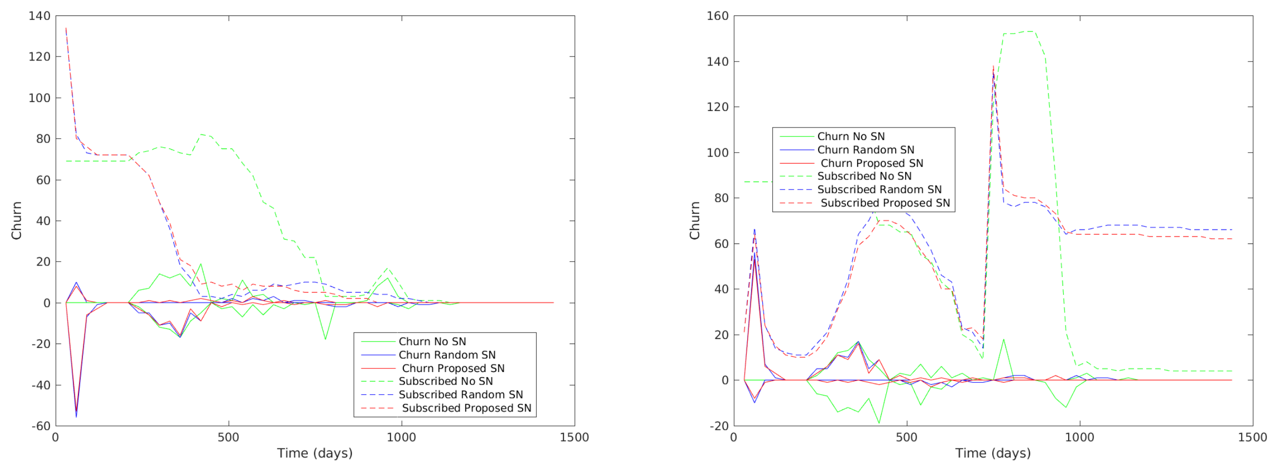
Figure 14: Video customers churn and subscriptions



(a) MNO 1

(b) MNO 2

Figure 15: Social customers churn and subscriptions



(a) MNO 1

(b) MNO 2

Figure 16: Work customers churn and subscriptions

	Billing	QoS	Data cap
Moderate	40	10	10
Gamer	30	40	30
Social	30	20	30
Music	20	30	20
Worker	10	40	30
Video	20	30	20

Table 9: Dissatisfaction step by 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
Music	0.50	0.40	0.10
Worker	0.80	0.10	0.10
Video	0.10	0.80	0.10

Table 10: Device probabilities for usage profiles

$$HETEROGENEITY_{iA} = 1 - \left[\sum_{1}^{n} \left(\frac{A_k}{en} \right)^2 \right]$$

where A is the attribute, in this case the usage profile. A_k the number of friends with usage profile k in the customer network. en is the number of friends in the ego network with valid data on A. And n is the total number of usage profiles of A represented in the customer network. Lower values mean higher number of friends with the same usage profile, and higher values mean a more heterogeneous customer network. Figure 17 shows boxplots of the heterogeneity in the network created by the original algorithm and the proposed algorithm.

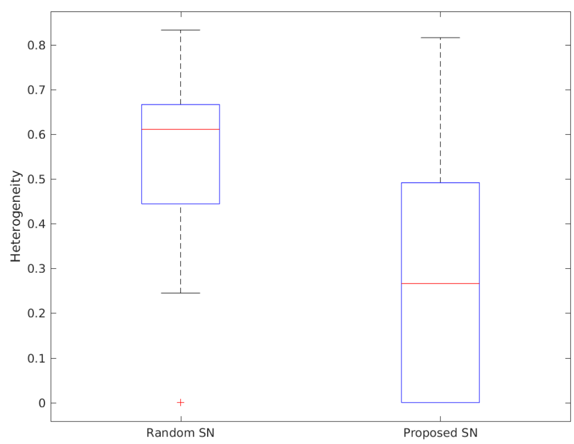


Figure 17: Heterogeneity

6. Conclusions

In the saturated telecommunications market, MNOs compete against each other to position themselves among customers. Churn is a problem that MNOs try to reduce by adopting retention strategies. However potential churners have to be identified before it's too late.

The mainstream approach to churn prediction considers each customer individually. Preliminary studies have shown, however, that members in the social circle of a subscriber also influence the subscriber to churn Dasgupta et al. (2008). Developing churn prediction systems that take social aspects into account poses an emerging theoretical challenge with potentially great practical implications.

Traditional methods use data mining techniques to identify potential churners, however they don't always provide with clear insights on churn reasons. We propose the use of ABM to model customers in the telecommunications market and in this way explore the effects of characteristics of both customers and MNOs, explain the causes of churn, and use it as a prediction tool for MNOs.

The proposed model includes demographic and psychographic characteristics, and dependencies among these characteristics. These characteristics and dependencies are shown, in the state of the art, to have a relation with the way customers behave in the mobile telecommunications market. The proposed model follows a well defined buying decision process that describes decision making and post-purchase behavior, which is the stage where customers decide to continue with a MNO or churn. On top of this, we take into account the social aspects that have to do with the flow of information and their effect on customers decisions. We use the work by Toivonen et al. (2006) to create a social graph that exhibits the features present in real life social networks and we propose a modification to this algorithm in order to take into account homophily.

We believe the inclusion of usage profiles to the model is very important since they introduce implicit needs, whether it is of the amount of data, QoS sensitivity or even price/data relation. This will differentiate usage profiles in their purchase and post-purchase behavior.

We showed with our experiments that taking into account social influence, the users find their ideal service quicker than when there is not flow of information between customers. Furthermore, we showed that taking into account homophily helps in customers find this ideal option at a more rapid pace. We also showed that using homophily in the algorithm proposed by Toivonen et al. (2006) effectively groups similar customers together.

We believe the proposed approach could be potentially useful to MNOs because it can be fed with any data. For example, already available data MNOs have from their customers could be fed to the model and with it explore hypothetical scenarios, i.e. test new pricing or marketing approaches. This will enable MNOs to evaluate more reliably new strategies before they are implemented in re-

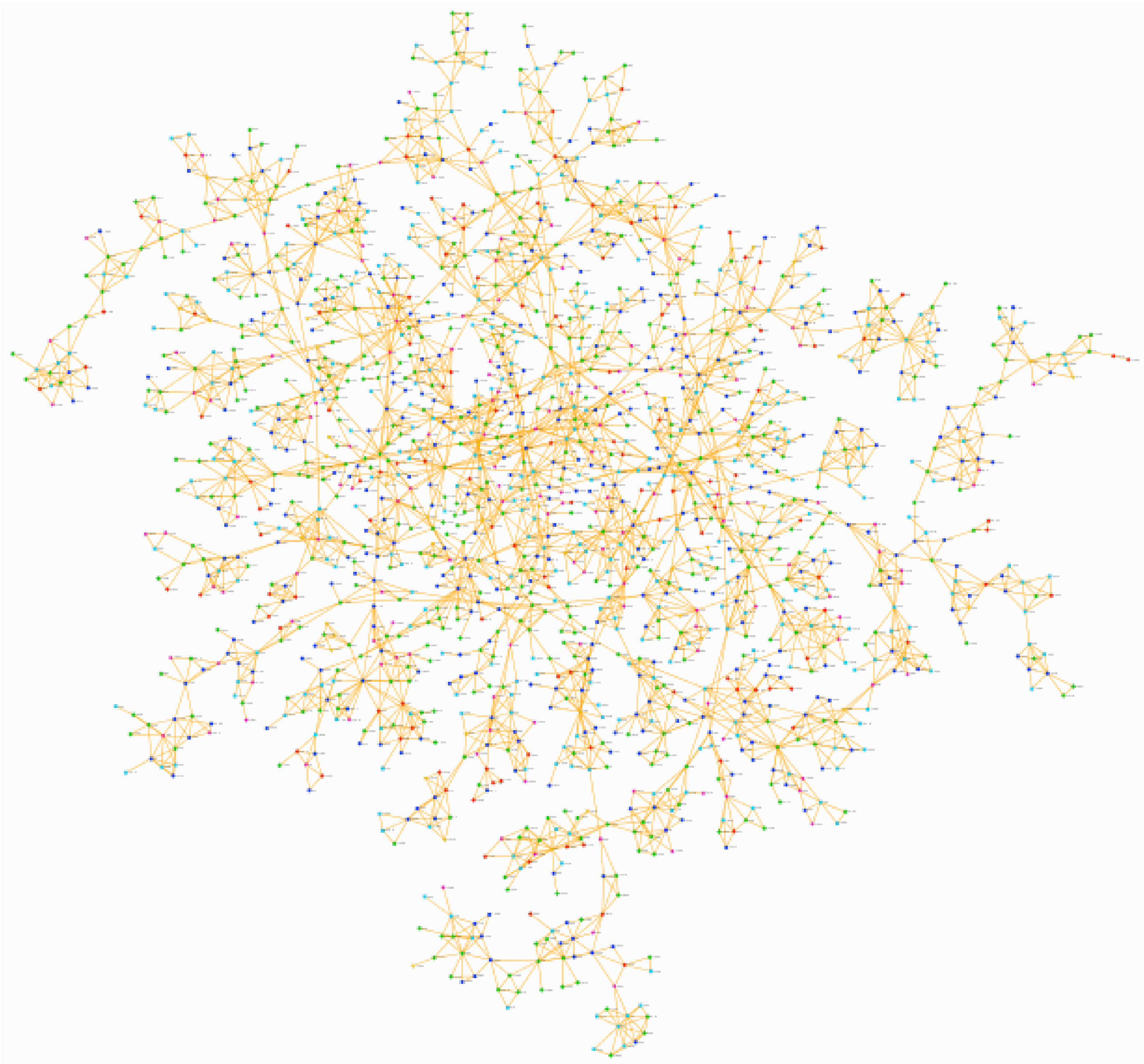


Figure 18: Network created with random social network generator

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

Table 11: Applications and devices

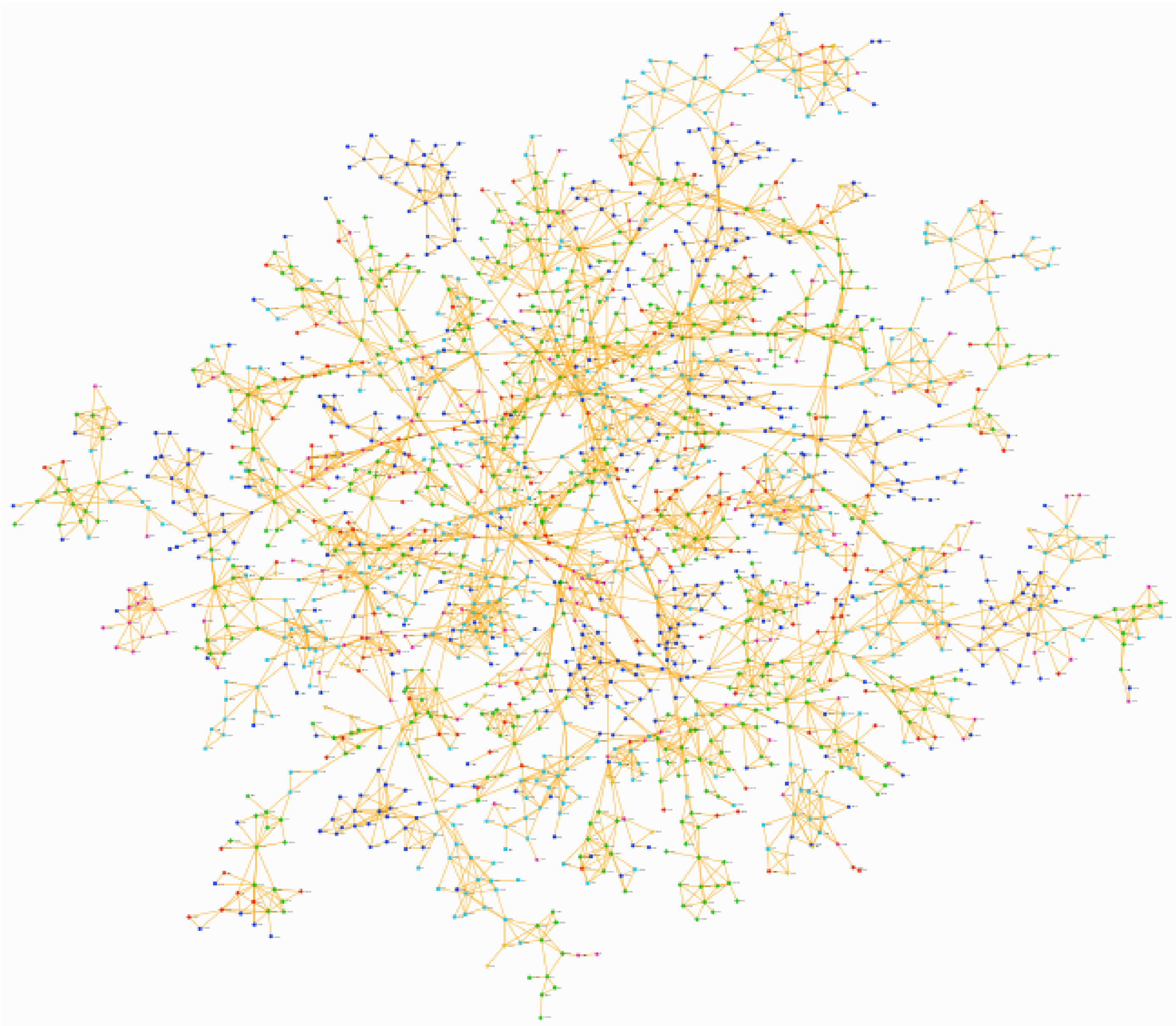


Figure 19: Network created with proposed social network generator

ality. The results obtained during experimentation will be specific to the data that was used to feed the model with.

Another potential benefit to MNOs is that, using this model will let them use the customer characteristics included in the model for segmentation purposes. This will let MNOs focus on specific subsets of customers to get insights on such segments that could be later used for decision making purposes. For example, an MNO could make use of these insights to create marketing and sell strategies directed towards specific customers. Also, MNOs could target or identify groups of customers with a risk to churn due to social influence and target these social circles in order to keep these customers.

As future work we see the experimentation on more complex scenarios. For example, multiple MNOs each offering multiple non equivalent service plans. Other opportunity for future work could be letting customers change and adjust their profiles overtime, so profiles are non static.

Acknowledgements

This work is partly funded by the Consejo Nacional de Ciencia y Tecnología (CONACYT) and FLAMINGO, a Network of Excellence project (318488) supported by the European Commission under its Seventh Framework Programme and the project TEC2015-71329-C2-2-R (MINECO/FEDER).

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