MOBILE NETWORK OPERATOR SWITCHING BEHAVIORS OF CUSTOMERS IN THE TURKISH TELECOMMUNICATIONS MARKET: AN AGENT-BASED MODEL

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DECLARATION OF ORIGINALITY

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ABSTRACT

Mobile Network Operator Switching Behaviors of Customers in The Turkish Telecommunications Market: An Agent-Based Model

In this study, Turkish mobile telecommunications market is modelled with a relatively new approach called Agent-Based modeling as it is flexible and able to be used for modeling complex systems. Especially over the last decade, it becomes crucial for mobile network operators to seek strategies for keeping their customers as there is a significant increase in customer switching rates in the market with the help of government rulings. Technological developments in the industry also make the competition between mobile network operators more intense as the number of customers are increasing year by year. The model proposed in this study uses agents as customers in the market and it is the agents in the system who make decisions of changing their mobile operators or staying in their current subscription according to possibilities obtained by multi – logit function at the end of each month. The real market data is taken from quarterly reports of Turkish Telecommunications Agency. The analysis of the experiment results shows that price parameter effects customer switching rates significantly. It can be found from the results that mobile operators with higher brand effect has less price sensitive customers so it can be proposed that mobile operators may try to increase their brand effects in order to have less price sensitive customers.

ÖZET

Türkiye Telekomünikasyon Pazarında Müşterilerin Mobil Operatör Değiştirme Davranışının Ajan Tabanlı Modellenmesi

Bu çalışmada, Türkiye telekomünikasyon pazarı görece yeni bir yaklaşım olan ajan tabanlı modelleme ile modellenmiştir ve kullanıcıların operatör değiştirme davranışları incelenmiştir. Bu yöntemin seçilmesinde ajan tabanlı modellemenin esnek ve karmaşık sistemlere uygulanabiliyor olması etkili olmuştur. Özellikle son on yılda, devletin koyduğu kolaylaştırıcı kuralların da yardımıyla mobil operatör değiştirme oranlarının artmasıyla birlikte, operatörler için kullanıcıları kendilerinde tutacak stratejiler geliştirmek çok önemli hale gelmiştir. Sektördeki teknolojik gelişmelerle birlikte pazara her yıl daha çok kullanıcının girmesi de mobil operatörler arasındaki rekabeti artırmıştır. Bu modelde ajanlar marketteki müşterileri temsil etmekte ve her ayın sonunda operatör değiştirme ya da kendi operatörlerinde kalma kararını çoklu logit fonksiyonundan elde edilen olasılıklara göre vermektedirler. Pazar verileri Bilgi Teknolojileri ve İletişim Kurumu'nun her çeyrek yayınladığı raporlardan alınmıştır. Deney sonuçlarının analizine göre, fiyat parametresi operatör değiştirme oranlarını önemli ölçüde etkiliyor. Sonuçlar ayrıca marka etkisi yüksek olan operatörlerin müşterilerinin fiyattaki değişimden daha az etkilendiğine işaret ediyor. Bu nedenle operatörlerin fiyata daha az duyarlı müşterilere sahip olmak için marka etkilerini artırmaya çalışmaları önerilebilir.

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CHAPTER 1

INTRODUCTION

As the number of customers increased drastically in the telecommunications market in parallel to technological advancements and ease of accessibility to mobile phones recently, keeping current customers and even gaining new ones has become more and more important in telecommunications industry. Mobile operators are paying attention to all customer segments and there is an intense competition between them. Switching from one operator to another is much easier comparing to past. Furthermore, Turkish government demand mobile operators to make it more comfortable for customers to compare their tariffs. Since 2007, it is possible for users to change their Mobile Network Operators (MNOs) without changing their phone numbers which is called phone number portability and increasing number of people benefit from this ruling since then as well.

There are three MNOs currently operating in Turkey namely Avea, Vodafone and Turkcell. According to the last quarterly report of BTK (Turkish Telecommunications Agency) as of December 2017, there are 77.8 million customers in total in the market which corresponds to 96.3% penetration rate. Turkcell has the biggest market share with 40.5% and Avea has the least share with 21.6% and while market share of Vodafone is 37.9%. The rate of the post – paid customers is 54.1% and the rest of the customers have pre – paid subscription. Post – paid subscription often requires a one-year liability period in which if the customers ends its subscription, he pays an additional price. The report also indicates that Turkey becomes the country with the highest value of monthly average calls made with 442 minutes among European countries. 4G/LTE technology, which allows high speed mobile data rates, is introduced to the market in the second half of 2015 and it affects data usage behavior of the customers significantly.

As it gets more difficult for the companies in the industry to retain their customers since the market becomes more fluid in the last decade, companies are driven to understand customer behavior with the extensive data they have. The mainstream approach for analyzing customer decisions are using data mining and statistical models. However, in this model a relatively new approach is used called Agent Based Modeling (ABM) in order to model MNO switching behavior of mobile customers as it can be applied to heterogonous structures and consider the system naturally. In ABM, agents stand for the actors in the modelled social environment who can interact with each other and make autonomous decisions. Agents in this research represent the customers in the market which has attributes such as age, subscribed MNO, mobile usage plans and subscription type.

This study aims at investigating switching behavior of customers in Turkish telecommunications market. The model analyzes last five-year period from January 2013 to December 2017 using quarterly BTK reports on Turkish telecommunications market as its data source. The reports present total number of ported numbers and net gain of the MNOs for each three – month period as well. At the end of each month in the simulation, agents calculate their utility for each switching and non – switching cases considering the switching cost, brand effect, price and data and call usage. Afterwards they make a decision of switching from one MNO to another or staying their currently subscribed MNO.

The model is implemented using NetLogo 6.0.3 and experiments are run with behavioral space tool. Once the behavioral parameters are calibrated with a calibration criterion, several analyses such as local sensitivity, global sensitivity and uncertainty are applied to the experiment outputs.

The remainder of this thesis is organized as follows. An extensive literature review about ABM and its applications to telecommunications markets is included in Chapter 2. Chapter 3 represents design of the model and simulation parameters in detail. Results of the analysis made in order to assess the model is presented in Chapter 4. Finally, in Chapter 5 the findings of the results further discussed and possible future advancements to the model are proposed.

CHAPTER 2

LITERATURE REVIEW

In this chapter, concept of ABM, agent definition, advantages and limitations of ABM and the modeling cycle is reviewed in the literature in the first place. Afterwards, the works related to customer churn analysis in telecommunications markets are discussed. Background of Agent-Based Modeling and Simulation (ABMS) applications applied to customer churn behavior is reviewed in the last place.

2.1 Agent-based modeling

Macal & North (2005) states that ABMS, which is a new way of modeling systems consisting autonomous and interacting agents, has a potential to have significant effects on how businesses use computers to support decision-making and researchers use electronic laboratories to support their research. Jackson et al. (2017) points out that ABM is a modeling technique, which is not frequently used but can help scientists test their hypothesis and establish theories by simulation of artificial worlds. ABM can be considered as a mindset rather than a technology, describing a system in terms of its basic components (Bonabeau, 2002). It can be defined as a computerized simulation of a number of decision-makers (agents) and institutions, which interact through prescribed rules (Farmer & Foley, 2009).

The agent perspective, which is taken viewing any system as consisting of agents, is the most important and distinguishing feature of ABMS. The crucial modeling elements of ABMS are the agent and its behaviors which affect the agent's own actions, the actions of other agents and the environment. (Macal, 2016). The term agent can be defined as a collection of autonomous decision – making entities in the modeled system. Each agent individually makes an assessment for its situation according to a set of rules and may show behaviors differing by the system they are used in such as producing, consuming and selling (Bonabeau, 2002). Agents may represent organisms, humans, businesses, institutions, countries or anything that has a definite objective and their interactions (Railsback & Grimm, 2012; Helbing, 2012). For instance, properties of an agent representing an individual may include his or her birth, death and reproduction, needs of resources, perception, emotions, competition and fighting ability, memory and expectations from the future etc. (Helbing, 2012). The most important features of agents can be listed as follows (Macal & North, 2005; Macy & Willer, 2002):

- An agent has an objective and his decisions are shaped accordingly.
- Agents are autonomous and they can make decisions independently in their environment and with their interactions with other agents.
- Agents are adaptive and backward – looking. Based on the experience they have, agents can adapt their behaviors and learn. Memory usage is required in these models.
- Each agent is a discrete individual and their behaviors and the decisions they make are determined by a set of rules. Characteristics of an agent is defined beforehand and it can be easily identified whether something is a part of an agent or not or it is a shared characteristic among all agents in the model.
- Agents are interdependent and interact with other agents. Agents may be affected by other agents which are also affected by some other factors in processes such as persuasion, sanctioning and imitation.

Helbing (2012) argues that currently most of the software simulations done in natural sciences are based on equation – based modeling which is definitely a difficult task to apply to social sciences since most of the system behaviors have not been represented mathematically. Gilbert & Terna (1999) point out that statistical and mathematical models have some drawbacks such as inability to illustrate real social phenomena since many of the equations can get way too complex to trace analytically. It is possible that the upper hands of mathematical formalization disappear, specifically when the model consists of non-linear relationships and yet these are prevalent in the social world. Epstein (2011) states that ABM can solve problems that analytical methods unable to solve especially in the area of physical and biological sciences and economics. Srbljinović & Škunca (2003) suggest that computer simulations are more suitable for representing theories of social science than most of the mathematical models especially the ones including closed form mathematical expressions. Agent-Based simulations can help us model a far wider range of non-linear behavior than conventional equilibrium models (Farmer & Foley, 2009).

The reason why ABM is being used extensively is the fact that the world we live in is becoming increasingly complex. As the systems that we work on are becoming more complicated with regard to their interdependencies, conventional methods are not now as applicable as in the past (Macal & North, 2007). Helbing (2012) states that Agent-based models can be combined well with other kinds of models. Bazghandi (2012) indicates that ABM is advantageous over other modeling approaches for the reason that it is a flexible, cost efficient and time – saving technique representing the emergent phenomena and describing the system naturally. Twoney & Cadman (2002) state that one of the strengths of ABM is the heterogeneity since the heterogeneous structure of agents allows us to have diversity in attributes and behaviors which is unlikely to have in traditional mathematical models. It is also easy to benefit from visualization in ABMs (Helbing, 2012). Caderman (1997) shows these additional advantages of using ABM:

- Ability of modeling frequently changing social parameters and the behavioral adaptation of the agents to these conditions. Changing conditions may also include death and birth.
- Ability of modeling rational agents, making decisions and acting in conditions of incomplete knowledge and information.
- Ability of modeling processes out of equilibrium.

It is obvious that ABM is not completely advantageous over other techniques and it has some drawbacks either (Robertson, 2005). According to Macal (2016), some of the challenges that ABMS faces are increasing credibility and transparency of the models, making software tools easier to use and figuring out the ways of developing more efficient models and using ABMS more effectively in order to get relevant data and analyzing model results. Crooks & Heppenstall (2012) see the nature of the model as another challenge for ABMs. For instance, in a system where agents are representing individuals there is a possibility of irrational behavior, subjective decisions and complex psychology. Twoney & Cadman (2002) argues that determining the rules of behaviors in ABM is a difficult challenge since it is not easy to capture the appropriate processes or mechanisms underlying the agents' behavior. It can also be noted as a problem for ABMs that Agent-Based software development kits have some performance issues especially when the researcher has to work with a large number of agents and the tools are not designed for extensive simulations (Bazghandi, 2012).

Jackson et al. (2017) studied the comparison of ABM and the other techniques by means of control and realism, scale, nonlinear dynamics and mechanism. Table 1 shows this comparison (Jackson et al, 2017).

Table 1. Comparison of ABM and The Other Techniques

	Field studies	**Lab experiment**	**Archival studies**	**ABMs**
Control and Realism	Low Control; High Realism	Medium Control; Medium Realism	Low Control; Medium Realism	High Control; Low Realism
Scale	Medium to High Scale	Low to Medium Scale	High Scale	High Scale
Nonlinear Dynamics	Medium Visibility	Low Visibility	Medium Visibility	High Visibility
Mechanism	Medium Clarity	High Clarity	Low Clarity	High Clarity

Constructing an ABM is similar to building any kind of model or simulation. Purpose of the model, questions to be answered and the potential users are determined in the first place. Afterwards, the model is analyzed systematically and the identification of basic elements and interactions between them, and related data sources is done (Macal & North, 2005). Helbing (2012) suggests that the concepts like the research question and the methodology, assumptions underlying the ABM, empirical and experimental evidence and the expected range of validity and limitations of the model need to be clearly addressed by the researcher. Salgado & Gilbert (2013) state that research in ABM has a series of actions like any standardized research process and in reality these actions can take place in parallel and the whole process is done iteratively while ideas are improved. Flow of the process is given in Figure 1 (Salgado & Gilbert, 2013).

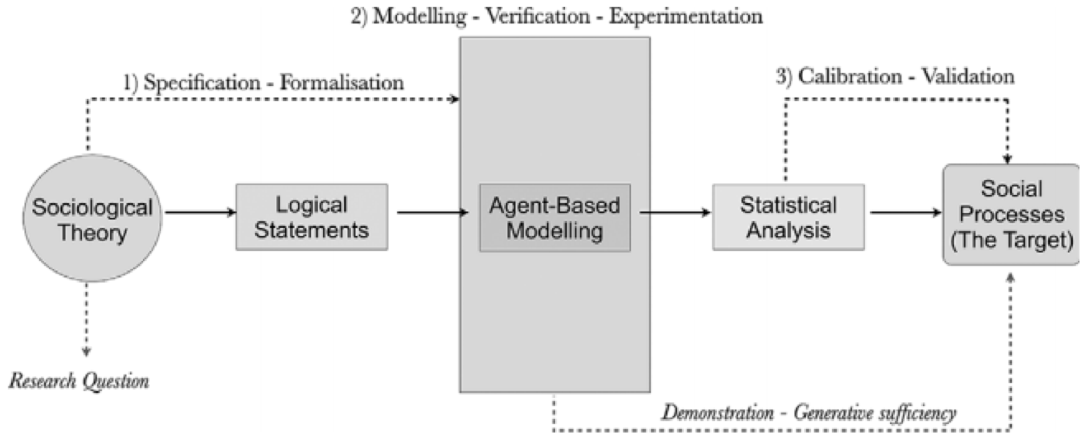

Figure 1. Flow of ABM research process

2.2 ABMS applications for telecommunications markets

Twoney & Cadman (2002) claim that telecom, IT and media industries has experienced a massive change in terms of demand, governmental rules and technology over the last decade which makes the market a lot harder to analyze for the researchers. It is likely that ABM allow us to analyze customer churn behavior better and overcome some of the disadvantages of data mining (Twoney & Cadman, 2002).

Hassouna & Arzoky (2011) applied ABMS to analyze customer retention in UK mobile market using AnyLogic as software development tool and named this model as CUBSIM (Customer Behavior Simulation). In the model, agents correspond to the customers and the services provided by mobile network operators and demographical factors shape the decisions of customers. External effects such as word of mouth is taken into consideration as well when constructing the model. Customer satisfaction is evaluated looking at the interaction between MNO and the customer and the demographic factors as well as comparing expectations and real-world results. At each time step, which represents one month in real time, customer decides whether he/she stays in his/her service provider or not according to the satisfaction level he or she has. The architecture of the model is given in Figure 2.

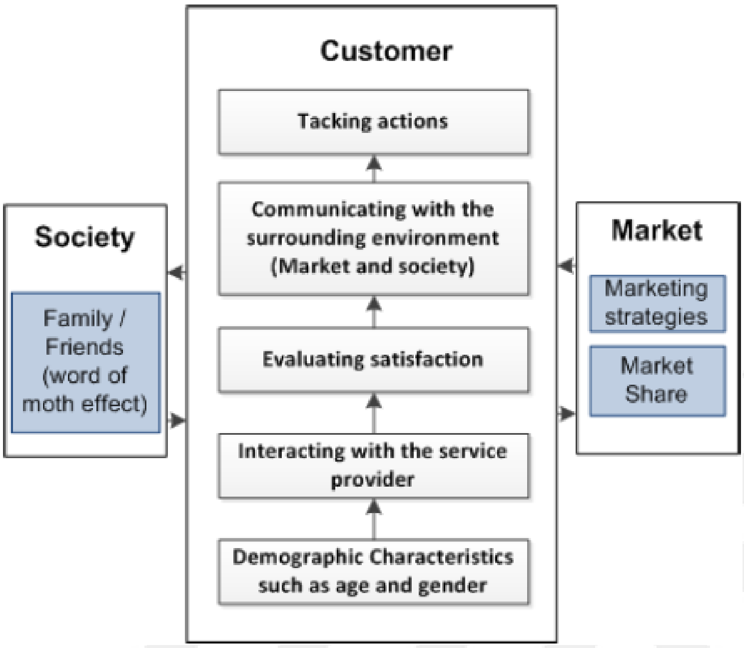

Figure 2. The architecture of the model of Hassouna & Arzoky (2011)

The Cubsim model is implemented to understand customer behavior in the UK mobile market. Mobile operator parameters are also included in the simulator screen and it is possible for the users to evaluate different scenarios with the model. Hassouna & Arzoky (2011) also point out that instead of taking MNOs as passive entities, it would give better results to consider them as active agents that can interact with the customers and act according to their needs.

Hayashi et al. (2011) implemented both ABMS and machine learning techniques to study churn in auto renewal services. Machine learning is mainly used for optimizing some of the key parameters in ABMS. In this work the customer information is retrieved from website of a subscription based security company. The proposed framework is presented in Figure 3:

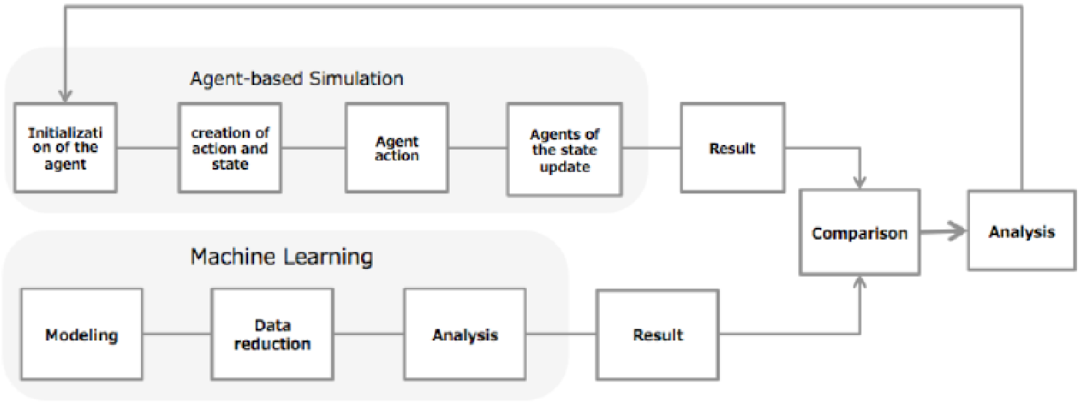

Figure 3. Architecture of combining machine learning and ABMS

The following assumptions are made for the customer behavior:

- Customers are most likely to churn close to the contract expiration date, especially after they receive the notification e-mail.
- Churn rate is directly correlated with the prices of the products customers subscribed to. Therefore average price of the service is included in the formulation for calculating churn rate.

After running the experiments, it is concluded that accuracy of the prediction is improved as machine learning is applied to obtain parameter values.

In a more recent research, Bell & Mgbemena (2017) analyzed customer data in mobile phone sector using ABMS. They proposed a novel data focused approach namely CADET (The Customer Agent Decision Tree) in which ABM and decision tree analysis are combined such that agents are determined by studying decision trees. In this research, CART (Classification and regression trees) algorithm is used while constructing decision trees. Bell & Mgbemena (2017) consider customer satisfaction, switching cost, relationship quality and price of the service as the key determinants of customer churn behavior in mobile services industry. In CADET method, they introduced four central concepts which are data selection and normalization, decision tree generation, tree interpretation and model building. Flow chart representation of CADET method is shown in Figure 4.

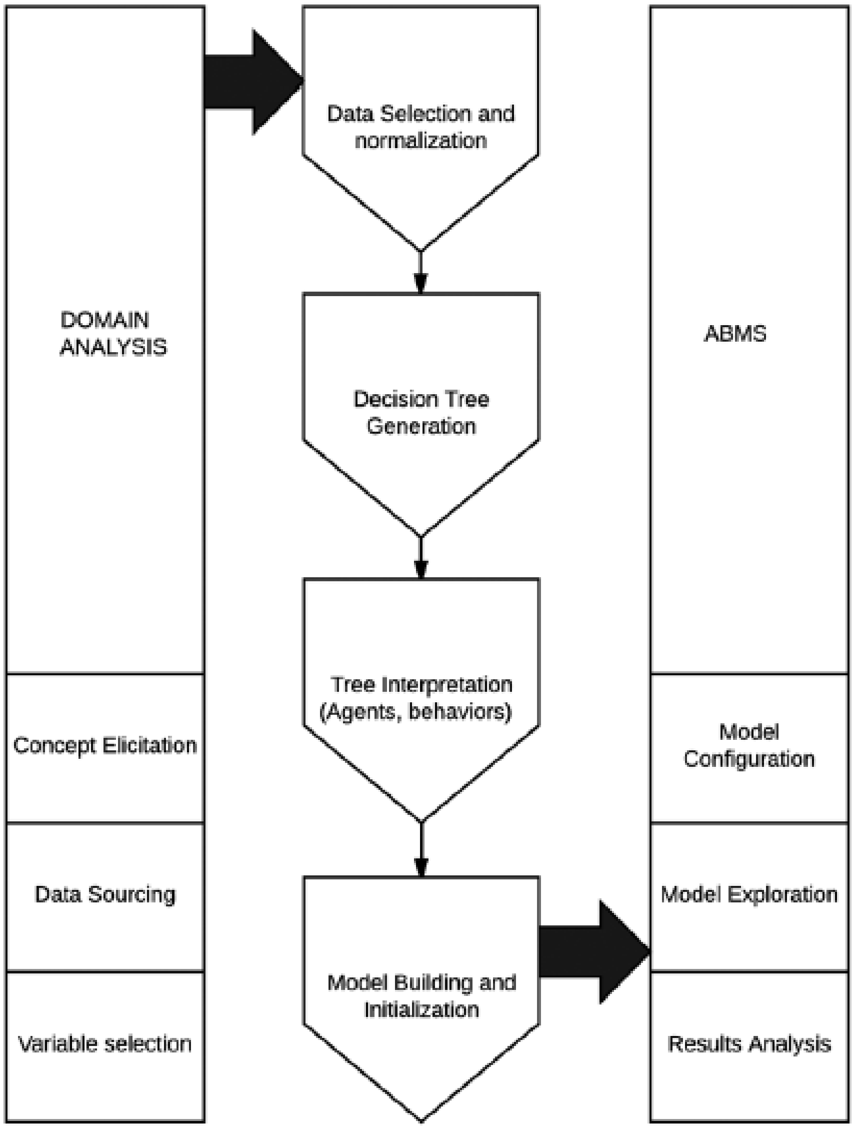

Figure 4. Illustration of CADET method

Bell & Mgbemena (2017) applied CADET to a real world dataset which they obtained from a UK telecommunications company. The dataset includes customer information such as gender, contract length, region and data and voice usage details of the customer. Experiment results shows that decision tree analysis provides ABM a clear description of agents and their attributes. CADET is also useful since it considers agents as heterogonous entities, and it can be applied to other industries.

Flores-Méndez et al. (2016) studied churn in MNOs applying ABM and considering demographic and psychographic characteristics of the customers. A user profile is defined for every customer and the entities in the profile can both be independent and dependent to other attributes. The relationship between different characteristics they come up with is shown in Figure 5.

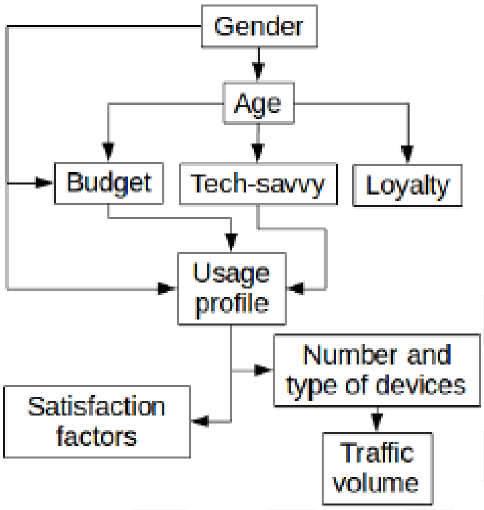

Figure 5. Relationship between characteristics of agents

It is also pointed out that churn of a customer affects the other customers around him or her and therefore social network analysis is applied as well. Homophily algorithm is used in social network generation as the similarity in the customer profiles increases the influence factor since it is assumed that if the profiles are similar, the customers share the same values. Customer profiles are split into six categories which are moderate, gamer, social, music, worker and video. The CADET model is given in figure 6.

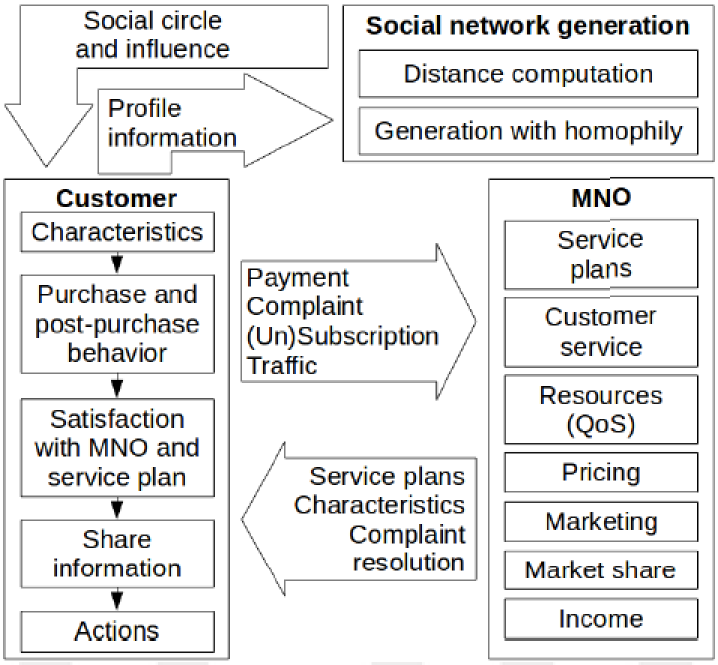

Figure 6. CADET model

The model is applied to a scenario where there are 2000 customers and 2 MNOs. The simulation, which is implemented on OMNeT++, is run for 1440 days and on the 720th day in the simulation, MNO2 decides to increment the bandwidth it offers to its customers. One of the conclusions from this work is that the users decide their ideal MNOs faster when the customer interaction exists in the system. The results also revealed that similar customers are grouped more effectively using homophily algorithm. MNOs can benefit from the model with the actual customer data and even construct new marketing strategies for specific customer segments.

2.3 Customer loyalty in telecommunications market

One of the earliest studies for customer loyalty in Turkish telecommunications market is done by Aydin & Ozer (2005). Using Structural Equation Modeling (SEM) they analyzed the data which is obtained from a questionnaire. It is proposed these hypotheses for customer loyalty:

There will be a positive relationship between,

- perceived service quality and customer loyalty,
- perceived service quality and trust in the operator,
- trust in the operator and perceived switching cost,
- trust in the operator and customer loyalty,
- corporate image and customer loyalty,
- perceived service quality and corporate image,
- perceived switching cost and customer loyalty.

The findings in the research supported these hypotheses. The results show that customer loyalty is mostly affected by trust in the operator and since perceived switching cost has an indirect effect on loyalty, it is more determinant than the service quality. It is also concluded that service quality is an important but not a sufficient parameter for customer loyalty.

Ahn et al. (2006) studied churn determinants in Korean telecommunications market. In the study the determinants of the customer churn is indicated as customer dissatisfaction, switching cost, service usage, customer status and its mediation effects. Ahn et al. (2006) claim that call drop rate plays an important role in customer churn decision. The study reveals that membership card programs are not significantly effective when it comes to reduce churn rates and customers who are more sensitive to promotions are more likely to churn and less brand loyal. Results show that if a customer uses a handset with advanced functions, it is less likely that this customer churns since customers can consider other mobile operators while looking for another handset. Ahn et al. (2006) also find out that churn rates go up as the number of complaints made by the customers increases.

In a more recent paper by Tiwari et al. (2017), customer churn behavior is analyzed and predicted in telecommunications industry by Naïve Bayes algorithm along with Apache Hadoop framework. Tiwari et al. (2017) consider average call minutes per day, number of plans and customer feedback as key parameters effecting churn decision. As a result of the paper, it is indicated that the model successfully predicts the customers who are about to churn and mobile operators may benefit from these results by applying their own data.

Yunus et al. (2012) made a research on relationship between service quality and customer loyalty in Malaysian telecommunications market. The entities which have an impact on service quality are identified as tangibles, reliability, responsiveness, assurance and empathy. In this study, data is gathered from a questionnaire and the respondents were mostly aged from 26 to 35 years old. The analysis points out that there is a significant relationship between service quality and customer loyalty. It is also concluded that responsiveness and empathy are not effective in predicting customer loyalty.

CHAPTER 3

MODEL

In this chapter, the model and the methodology of the study are presented in detail. Model structure is presented mostly based on ODD (Overview, Design and Details) protocol which is developed by Grimm et al. (2006) as a method used for standardizing the descriptions of Individual-Based and Agent-Based Models. The main purpose of ODD is providing a template to represent the model in three sections which are overview, design concepts and details. It becomes essential to use this protocol for ABMs as it makes it easier to read and write model descriptions and covers simple and complex models from different domains. Grimm et al. (2010) further claim that ODD helps ABMs to be easier to reproduce since it is a common criticism for ABMs not being reproducible. General protocol structure of the ODD is shown in Table 2.

Table 2. ODD Protocol Description (Grimm et al., 2010)

Overview	Purpose
	State Variables and Scales
	Process Overview and Scheduling
Design Concepts	Basic Principles, Emergence, Adaptation, Objectives, Learning, Prediction, Sensing, Interaction, Stochasticity, Collectives, Observation
Details	Initialization
	Input Data
	Submodels

The first part in the ODD protocol, overview section, gives the main purpose and general structure such that it is clearly understood by the reader what the model is focused on primarily and how the model can be designed in an object oriented way (Grimm et al., 2006). Polhill et al. (2008) claim that this section also provides an outline of the model including state variables, scales, process overview and scheduling. Design concepts element provides a link between the designed system and general concepts in the field of study. Details section is the last part of the protocol in which technical details of the model is revealed in three subsections which are initialization, input and submodels (Grimm et al., 2006).

3.1 Overview

As the regulations of Turkish government and the new standards in telecommunications market let customers to switch from one operator to another almost effortlessly, the market becomes more fluid and it becomes more essential for MNOs to keep their customers and even gain more. According to Lee et al. (2001), every year MNOs are unable to keep %30 of their customers approximately. It is an important question for MNOs and market analysts that what drives people into changing their service providers and at what extent these parameters effect customer behavior.

In this study, it is aimed to model operator switching behavior in Turkish telecommunications market using ABM approach. The reason why ABM is used as a modeling technique is that the market consists of heterogonous agents and it is inefficient to analyze this complex social phenomenon with linear equations or other conventional methods. In order to have a better understanding on dynamics of the market, key parameters and their effect on customer decisions will be investigated.

Each agent has a number of entities effecting his or her switching behavior which are given with descriptions in Table 3.

Table 3. Description of Entities of The Agents

Entity	Description
Operator	Currently subscribed MNO
Internet	Monthly Internet usage of the customer (Mb). Quarterly data usage data will be used for determining the distribution.
Call	Monthly call usage of the customer (Mn). Quarterly MoU data will be used determining the distribution for each operator.
Age	Age entity will determine whether the customer can be categorized as young or not. It also effects switching cost. It is obtained from demographic distribution of Turkey.
Subscription Type	Pre-Paid or Post-Paid. Quarterly subscription type rates are used
Remaining Liability Period	It represents how much time left in months for an agent to end his or her liability period only for agents with the subscription type post – paid. The value will be 0 otherwise.

Market data is retrieved from quarterly reports of Turkish telecommunications agency, namely BTK (Bilgi Teknolojileri ve İletişim Kurumu), which is responsible for making regulations for telecommunications industry in Turkey. The reports contain detailed information on telecommunications market including total number of customers and their subscription types, market share of operators, MoU (Minutes of Usage), mobile data usage rates, churn rates and statistics of operator switching with phone number portability.

There are three mobile operators currently operating in Turkey namely Turkcell, Vodafone and Avea. MNOs can be considered as proto – agents which means that although MNOs are not seen as agents in this work, further research may list them as agents. MNOs have a “Brand Effect” according to their number of customers and their market share. They also have two price parameters called k_{call} and $k_{internet}$ for call usage and internet usage of the agents respectively.

Scheduling is done in every month although the parameter calibrations will be realized in every three-month period since BTK announces reports quarterly. At each time tick in the simulation, new agents are created according to total number of subscribers analysis and they are distributed to different MNOs according to their market share at the time. They are affiliated with a subscription type with respect to the subscription type rates of the corresponding MNO. At the end of each month, agents predict their internet and call usage according to the prediction functions of MoU and data usage which are found by using real world market data. After anticipating their call and internet usage values, agents calculate their utility as well as the price he or she will pay for all the possible switching actions and for not switching at all. At this point, switching cost, which is dependent to agent’s age and liability period, is applied for the actions involve switching. Brand effect of the MNO is also taken into account for the agent’s behavior. Finally, agents assess an overall utility value and with a multi logit function possibilities of the actions and agent behavior are determined. Illustration of the model is given in the flow chart in Figure 7.

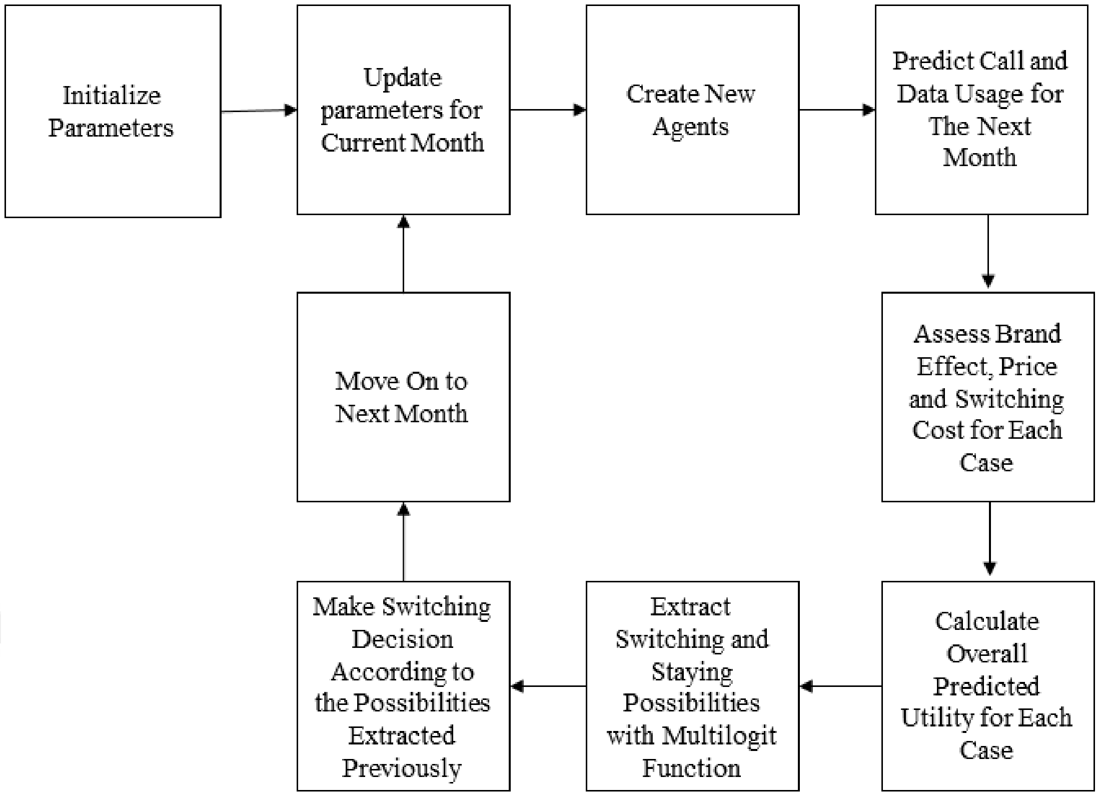

Figure 7. Flow of the constructed model at each time period

3.2 Design concepts

Grimm & Railsback (2005) point out that in a model; parameters, entities and functional relationships have to be based on a group of predefined concepts. For the reason that differential equations are unable to give a conceptual framework for ABMs, a general framework taken from Complex Adaptive Systems can be used to describe the concepts for ABMs such as emergence, sensing, observation, adaptation, objective and prediction (Grimm & Railsback, 2005).

As a switching behavior principle, main objective of the agents is to get maximum overall utility from their operators. These assumptions are made for the relationships between overall utility function and parameters in the system:

- The utility taken from call and internet usage effects the overall utility positively.

- Brand effect of the MNO effects the overall utility positively.
- Switching cost effects the overall utility negatively.
- The price agent pays for the month effects the overall utility negatively.

SMS (Short Message Service) is not included as a significant parameter effecting overall utility since IMS (Instant Messaging Service) largely replaced it over the last decade. Church & Oliveira (2013) predict that there will be a serious decrease in SMS usage as smartphones continue evolving and IMS services are cost effective and convenient. The functionality of IMS is in the scope of internet usage in this model.

Ahn et al. (2006) defines switching cost as a sum of reasons keep customers from changing their service providers effortlessly. They further indicate that for telecommunications market the most important parameters affecting switching cost are accumulated loyalty points and membership benefits. Bloemer et al. (1998) indicates that apart from the costs involves money, switching service providers may cause loss of time and has some psychological consequences for the customer since there will be an uncertainty with the new service provider. It is assumed that these factors are easier to overcome for young people. Hence the switching cost for the subscribers increases with the age of the agent. Another factor effecting switching cost is the liability of post – paid subscriptions as the operators charges customers more if the customer ends his or her subscription before the end of the liability period.

Brand effect includes MNO specific parameters such as service quality and corporate image. Brand effect is higher for the MNOs having more customers which means the higher the market share of the operator gets, the higher the brand effect value it has.

The concept of sensing is defined as internal and environmental state variables that agents are expected to be sensing, influencing the decision making process (Grimm et al., 2010). Sensing is applied to the model as the agent senses brand effect and the prices.

Prediction takes place at the end of each time tick as the agent anticipates the utility it expects for each subscription type available for him or her. In the model, there are 12 subscription types since,

- an agent can be subscribed to one of three MNOs,
- an agent can be below 25 years old or not,
- an agent can be a pre-paid or a post-paid subscriber.

There are six subscription types are available for each agent to choose from as there are two age categories namely young and adult.

Stochasticity is applied to the model at several points. Firstly, there is a random value uniformly distributed between 0 and 1 in the calculation of utility functions for the call and internet. Secondly, the prediction of the call usage for the next time tick uses a uniformly distributed value. Finally, multinominal logit function is used for determining the probabilities of agent decision at the end of each tick and decision is made accordingly.

For each time period, it is observed that the agents switch or stay in their MNOs. There is also a probability that an agent can stay in its MNO and switch between subscription types, from pre-paid to post-paid or vice versa. Analyses such as calibration, robustness and sensitivity are done in every three months according to the quarterly data of BTK. The design concepts like emergence, adaptation, collectives, learning and interaction are not included in this work.

3.3 Details

Grimm et al. (2006) indicate that details, the last section in ODD, shows the information which are not included in overview section. It answers the questions like how the state variables are initiated, what the environmental conditions are and what the submodels used in the overall model include. According to Amouroux et al. (2010), it also presents the crucial information for readers in depth to fully comprehend and to be able to re-implement the model in its entirety. All the parameters used in calibration analysis, regression analysis, price and brand effect are represented in Table 4, Table 5 and Table 6 respectively.

Table 4. Overview of The Calibration Parameters and Their Descriptions

Parameter	Description
$k_{sc_{age}}$	Age coefficient of the switching cost function
$k_{sc_{liability}}$	Liability parameter of the switching cost function
k_{price}	Price coefficient
a_{price}	Regression coefficient of price
BE	Brand effect parameter

Table 5. Overview and Description of The Regression Analysis Parameters

Parameter	Description
t	Time value of the simulation
Y_{nos}	Number of subscribers function
a_{nos}	Regression coefficient of the number of subscribers
b_{nos}	Intercept value of number of subscribers
Y_{noa}	Number of agents function
$Y_{ms_{operator}}$	Market share function of the MNO
$a_{ms_{operator}}$	Regression coefficient of the market share of the MNO
$b_{ms_{operator}}$	Intercept value of the market share of the MNO
$Y_{MoU_{operator}}$	MoU function of the MNO
$a_{MoU_{operator}}$	Regression coefficient of the MoU of the MNO
$b_{MoU_{operator}}$	Intercept value of the MoU of the MNO
$Y_{DUR_{category}}$	Data usage rate function of the data usage category
$a_{DUR_{category}}$	Regression coefficient of the data usage rate of the category
$b_{DUR_{category}}$	Intercept value of the data usage rate of the category
$Y_{SR_{SubscriptionType}}$	Subscription rate function of the subscription type
$a_{SR_{SubscriptionType}}$	Regression coefficient of the subscription rate of the subscription type
$b_{SR_{SubscriptionType}}$	Intercept value of the subscription rate of the subscription type
$MoU_{t_{operator}}$	MoU value of the agent at time t
k_{noa_0}	Initial number of agents

Table 6. Overview and Description of the Price and Brand Effect Parameters

Parameter	Description
$k_{BasePrice_{operator}}$	Base price parameter of the corresponding MNO
$k_{PriceInternet_{operator}}$	Data usage price coefficient of the MNO
$k_{PriceCall_{operator}}$	Call price coefficient of the MNO
$k_{AgeDiscount}$	Discount parameter for young customers
$k_{NewCustomerDiscount}$	Discount parameter for new customers
$k_{PostPaidDiscount}$	Discount parameter for post – paid customers
$k_{BEcoefficient_{operator}}$	Brand effect coefficient of the MNO

In this section, initial state of the entities of the agents, values of the previously described parameters and the input data used for determining the coefficients in the model are presented in the first place. Submodels and the formulation used in the simulation are given afterwards.

3.3.1 Initialization and input data

Initial conditions are determined according to the BTK reports on market data for the last five – year period from the first quarter of 2013 to the last quarter of 2017 having 20 distinct reports in total. There are 1000 agents representing the customers in the market initially and agents are created every month as the population in the mobile telecommunications market increases over the years. Number of agents to be created is determined according to the regression analysis of the total number of mobile subscribers' data. The change of total number of subscribers over five – year period is shown in Figure 8.

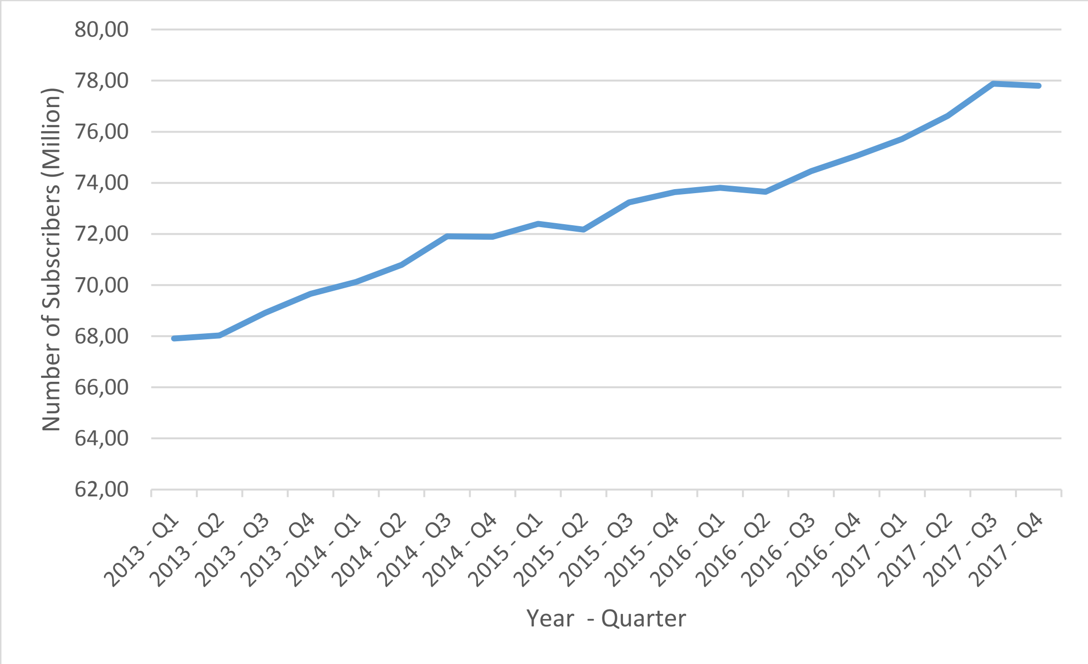

Figure 8. Total number of subscribers in the market per quarter

In order to model this data, linear regression analysis is applied. All the regression analysis used in the model assumes that quarterly results show the data in the middle of corresponding quarter meaning that Q1 shows the data of February, Q2 shows the data of May, Q3 shows the data of August and Q4 shows the data of November. t_0 corresponds to January of 2013. Data is formulated with linear regression as follows:

$$Y_{nos} = a_{nos}t + b_{nos}$$

Number of agents, Y_{noa}, is scaled as follows with respect to Y_{nos} using initial number of agents coefficient, k_{noa_0}:

$$Y_{noa} = \frac{k_{noa_0}}{b_{nos}} Y_{nos}$$

The coefficient values from the output of the analysis is presented in Table 7.

Table 7. Number of Subscriber and Number of Agent Coefficients

Parameter	Value
a_{nos}	$10^6 x 0{,}166$
b_{nos}	$10^6 x 67{,}876$
k_{noa_0}	1000

Newly created agents will be distributed to MNOs according to their market share data. Market share of the MNOs are given in Figure 9.

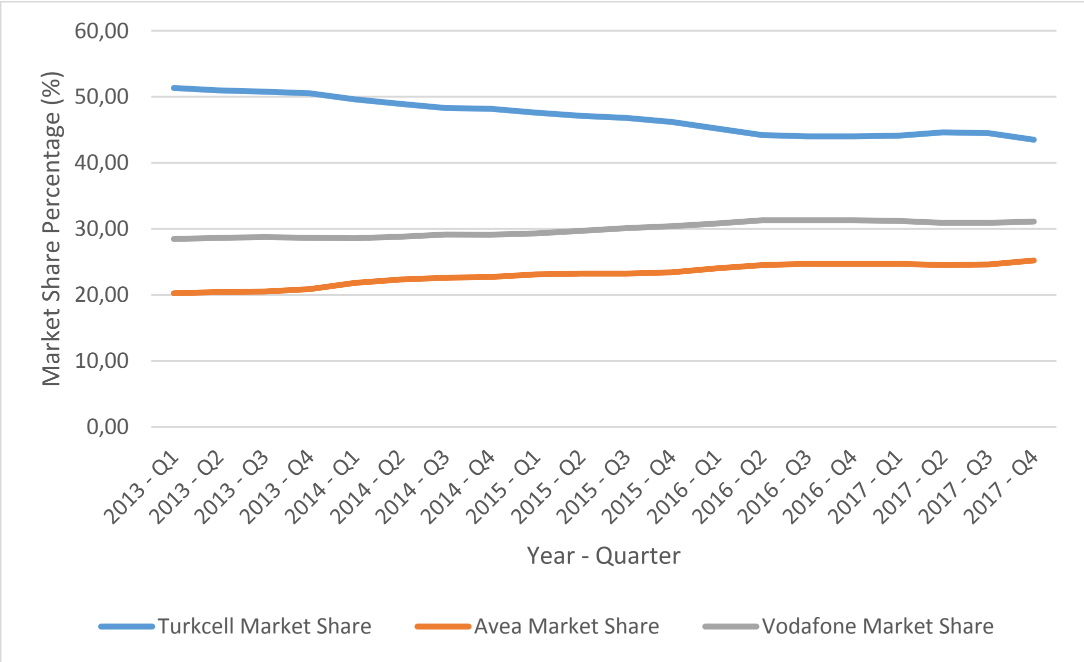

Figure 9. Market share of MNOs

Market share of Avea and Vodafone are analyzed with linear regression. Prediction of the share of Turkcell is calculated from the share of the rest of the mobile operators. Market share parameter values in Table 8 are obtained with following equations:

$$Y_{ms_{operator}} = a_{ms_{operator}} t + b_{ms_{operator}}$$

$$Y_{ms_{turkcell}} = 100 - (Y_{ms_{avea}} + Y_{ms_{vodafone}})$$

Table 8. Values of Parameters for each MNO

Parameter	Turkcell	Vodafone	Avea
$a_{ms_{operator}}$	-	0,059	0,088
$b_{ms_{operator}}$	-	28,178	20,470

Age of the customers are distributed according to the demographic data of Turkey for the year 2017 which is represented in Figure 10.

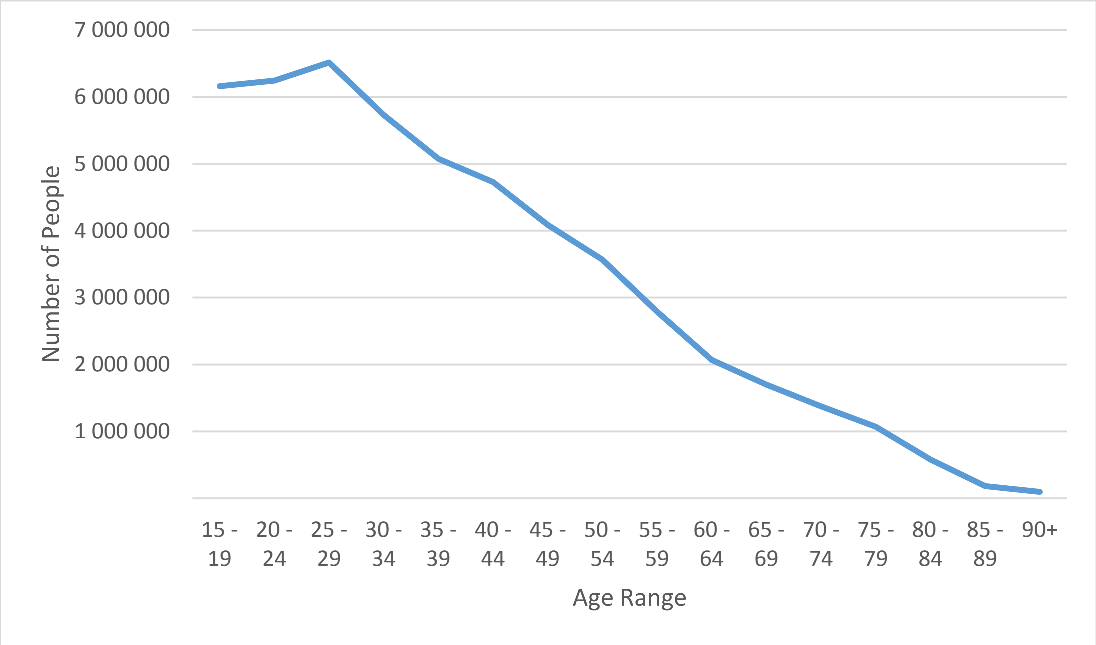

Figure 10. Demographic statistics of Turkey (TUIK, 2017)

Minimum age is assumed to be 15 while maximum age is determined as 100 for the model. Aging of the agents is not applied to the model since it will not affect the model significantly as there are also new agents. Ages are distributed uniformly between the age ranges.

Call entity of the agents is determined by modeling MoU data. Figure 11 shows the MoU values per operator in the simulation period.

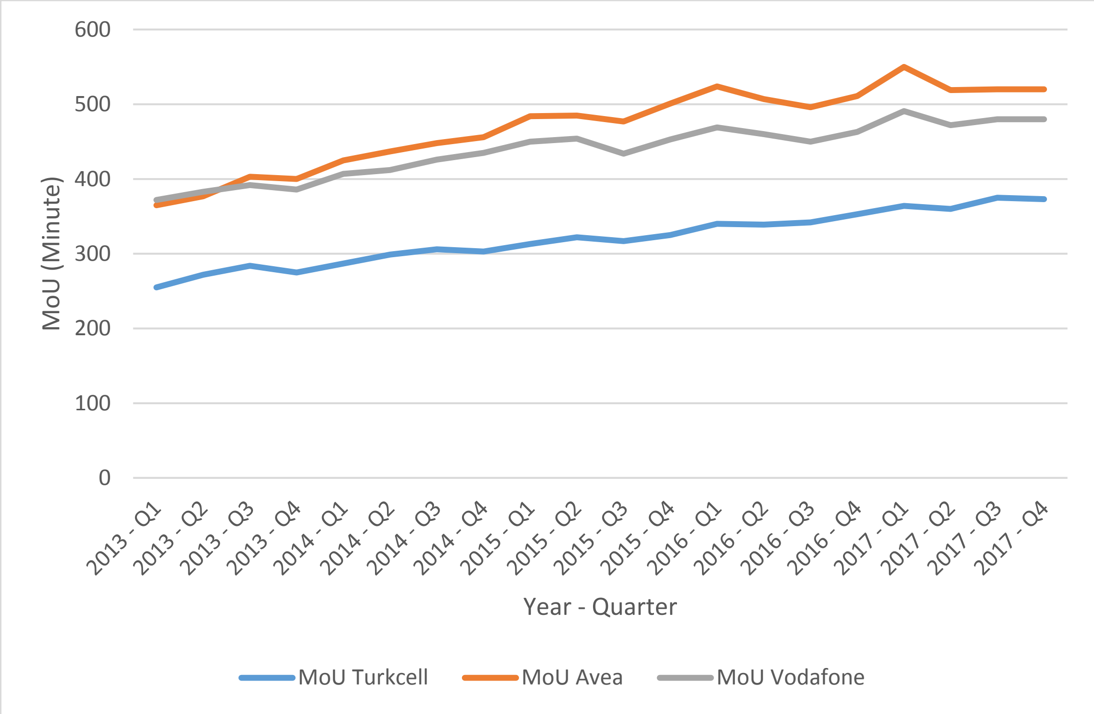

Figure 11. MoU values of MNOs

Regression analysis is applied for MoU values for each operator and regression parameter values represented in Table 9 are obtained with the following equations:

$$Y_{MoU_{operator}} = a_{MoU_{operator}} * t + b_{MoU_{operator}}$$

Table 9. MoU Regression Coefficients and Intercept Values for each MNO

Parameter	Turkcell	Vodafone	Avea
$a_{MoU_{operator}}$	1,967	1.910	2,842
$b_{MoU_{operator}}$	262,161	382,104	386,415

At the creation stage of the agents, monthly call usage values are distributed with random poisson distribution having a mean value of $Y_{MoU_{operator}}$. At the end of every month agents will determine their MoU values according to the following equation:

$$MoU_{t+1_{operator}} = MoU_{t_{operator}} + Uniform(0, 2 * a_{MoU_{operator}})$$

Data usage entity of the agents is determined by modeling the distribution of the Turkish telecommunications market internet data usage rates over the years which is shown in Figure 12. Although the report presents the data usage rates in ten categories, number of data usage rate groups defined in the model is five for simplification. It can be seen that rates of the higher data usage goes up quarter by quarter as new technologies such as LTE (Long Term Evolution) speed up the download rates up to 300 megabit per second.

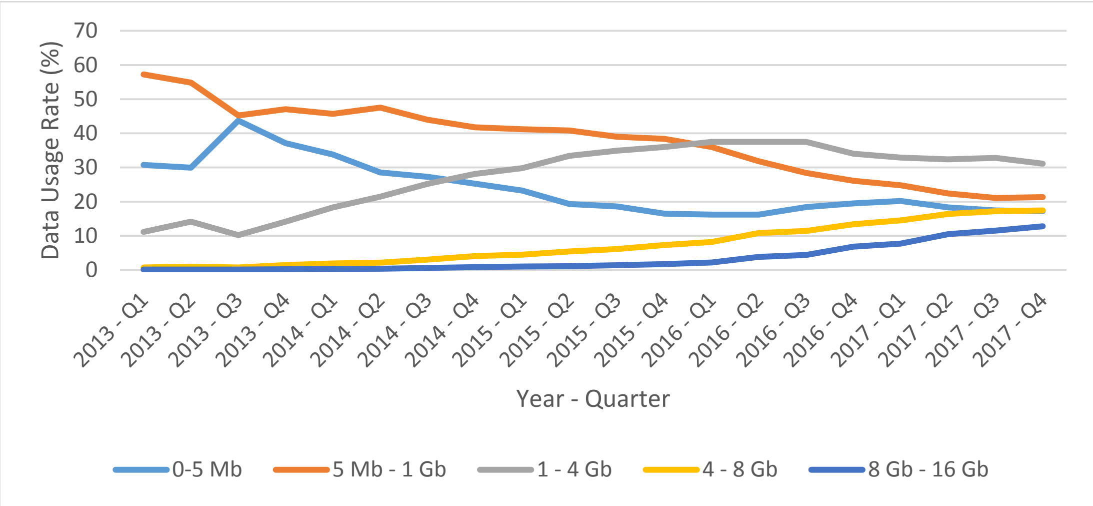

Figure 12. Mobile data usage rates

Percentages of the groups are identified with regression analysis applied to this data except for the last category as its rate will be effected by other category's rates. Data usage rate equations determined from the output are presented as follows:

$$Y_{DataUsageRate_{category}} = a_{DataUsageRate_{category}} * t + b_{DataUsageRate_{category}}$$

Regression parameter values for data usage are presented in Table 10.

Table 10. Regression Coefficient and Intercept Values of Data Usage Categories

Parameter	0 – 5 MB	5MB – 1GB	1 – 4 GB	4 – 8 GB	8 – 16 GB
$a_{DUR_{category}}$	-0,367	-0,601	0,437	0,324	-
$b_{DUR_{category}}$	34,685	55,473	14,742	-2,176	-

Data usage values of newly created agents are determined with respect to linear regression parameters. Data usage prediction for the next simulation tick is realized considering the average data usage statistics in simulation period which is presented in Figure 13.

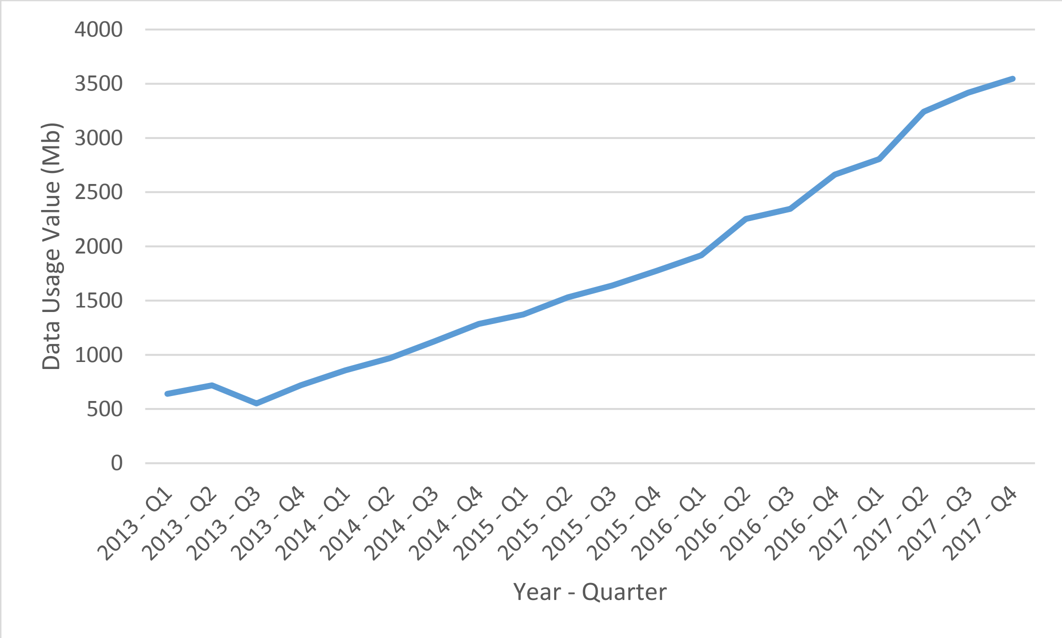

Figure 13. Average data usage rate

Applying linear regression analysis to average data usage of the agents, the following equation and the parameter values in Table 11 are obtained.

$$Y_{AverageDataUsage} = a_{AverageDataUsage} * t + b_{AverageDataUsage}$$

Table 11. Regression Coefficient and Intercept Values of Average Usage

Parameter	Value
$a_{AverageDataUsage}$	53,444
$b_{AverageDataUsage}$	192,126

At the end of the month, agents predict their data usage according to the following formula.

$$DU_{t+1_{agent}} = DU_{t_{agent}} + Uniform(0, 2 * a_{AverageDataUsage})$$

Since an agent can be either pre-paid or post – paid customer, it is also needed the real market data distribution for each subscription type. The trend shows that rate of the post – paid customers are increasing over the years. The subscription type data is represented in Figure 14.

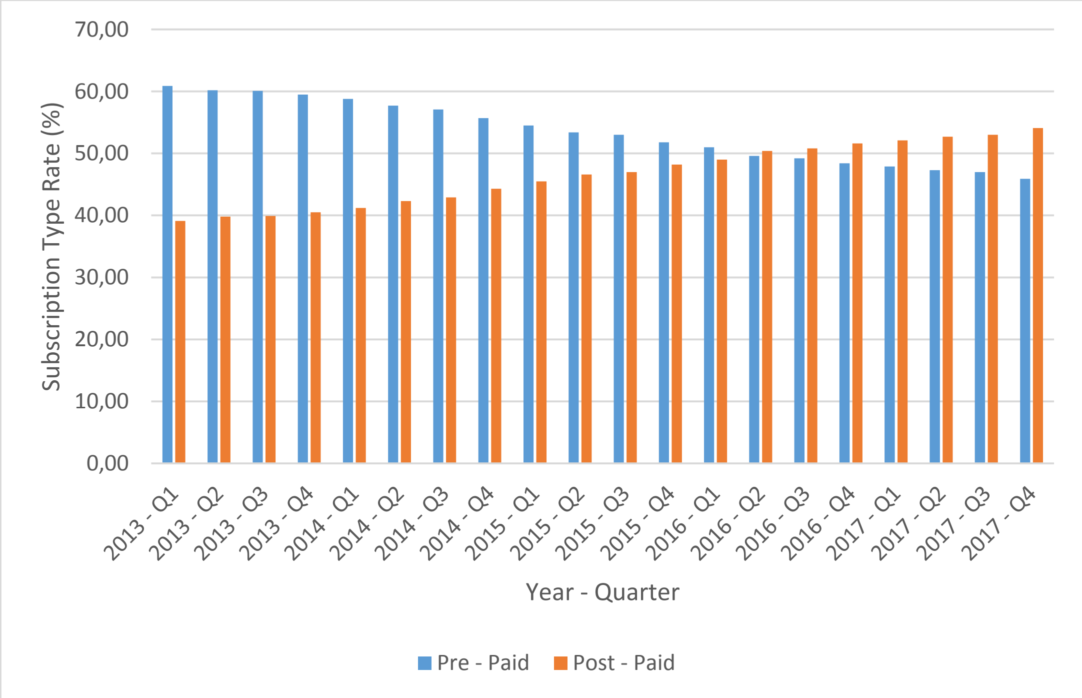

Figure 14. Subscription type rates per quarter

Regression analysis is applied to pre – paid customer rates. Post – paid rates will be determined using this analysis. Subscription rate formulas are obtained as follows:

$$Y_{SR_{SubscriptionType}} = a_{SR_{SubscriptionType}} * t + b_{SR_{SubscriptionType}}$$

$$Y_{SR_{PostPaid}} = 100 - Y_{SR_{PrePaid}}$$

Regression parameters for subscription rates are shown in Table 12.

Table 12. Regression Coefficient and Intercept Values of Subscription Rates

Parameter	Pre – Paid	Post – Paid
$a_{SR_{SubscriptionType}}$	-2,283	-
$b_{SR_{SubscriptionType}}$	61,787	-

Subscription types of the newly created agents will be defined according to the rates of the corresponding month.

Price coefficients for the MNOs are determined by analyzing current tariffs of the MNOs. It is observed that MNOs have a base price, namely $k_{BasePrice_{operator}}$, which is independent of the usage pattern of the subscribers. They also charge their customers for their data and call usage using the parameters $k_{PriceInternet_{operator}}$ and $k_{PriceCall_{operator}}$. MNOs apply discount for customers below certain age, post – paid subscriptions and prospected customers which are represented with $k_{AgeDiscount}$, $k_{PostPaidDiscount}$ and $k_{NewCustomerDiscount}$ respectively. It is also observed that as the technology advances, prices go down and for that reason, coefficient of $\left(1 - a_{price} * t\right)$ is added to the equation. Price formula is given as follows.

$$Price = k_{price} * \left(1 - a_{price} * t\right) * \ k_{AgeDiscount} * \ k_{PostPaidDiscount} * k_{NewCustomerDiscount} * (k_{BasePrice_{operator}} + \ k_{PriceInternet_{operator}} * q_{data} + \ k_{PriceCall_{operator}} * q_{call})$$

Agents in the system predict the price they will pay for the next month for each individual case. For instance, if a customer aged below 25 years is currently a Turkcell user and predicting the price he will pay for the next month in case he switches to a post – paid subscription of Vodafone, he will be benefitting all three discounts. Analyzing the tariffs of the MNOs from the data of their official websites, values of the price and discount parameters are extracted as in Table 13.

Table 13. Price and Discount Coefficients for each MNO

Parameter	Turkcell	Vodafone	Avea
$k_{BasePrice_{operator}}$	10	10	10
$k_{PriceInternet_{operator}}$	5	3	2.5
$k_{PriceCall_{operator}}$	5	3.5	3
$k_{AgeDiscount}$	0.80		
$k_{PostPaidDiscount}$	0.95		
$k_{NewCustomerDiscount}$	0.90		

Brand effect coefficient is calculated by scaling average values of the market share of MNOs. The coefficient values are listed in Table 14.

Table 14. Brand Effect Coefficient for each MNO

Parameter	Turkcell	Vodafone	Avea
$k_{BEcoefficient_{operator}}$	1	0,636	0,490

3.3.2 Submodels

At the end of every time period, each agent calculates its expected utility for the next interval and makes a switch or stay decision using a multi logit function. There are five components effecting overall utility which are call usage, internet usage, brand effect, price and switching cost. Submodel functions and parameters are presented in Table 15.

Table 15. Overview of Submodel Functions, Parameters and Their Descriptions

Parameter	Description
$U_{overall}$	Overall utility function
U_{call}	Utility function of the call entity of the agent
$U_{internet}$	Utility function of the data usage entity of the agent
SC	Switching cost function
$BE_{operator}$	Brand effect function
$Price$	Price function of the agent
x	Variable that is used in utility functions of the call and internet entity.
P_i	Probability of switching type, calculated using logit function
q_{call}	Value of monthly call usage of the customer in minutes
q_{data}	Value of monthly data usage of the customer in megabytes

Agents benefit from internet and call usage every month according to their call and internet entity values. Utility functions for call and internet are formulated as follows.

$$U_{call} = k_{call}\left(1 + (2 * Uniform_{0,1} - 1)x\right)\sqrt{q_{call}}$$

$$U_{internet} = k_{internet}\left(1 + (2Uniform_{0,1} - 1)x\right)\sqrt{q_{data}}$$

Brand effect function is depended on a calibration parameter, namely $BE,$ and an operator specific brand effect coefficient. The equation of the brand effect is given as follows:

$$BE_{operator} = k_{BEcoefficient_{operator}} * BE$$

Switching cost function, which is represented below, is effected by the age of the agent as well as switching cost and liability parameters. Liability is considered only if the agent is a post – paid subscriber.

$$SC = k_{sc_{age}} \sqrt{age_{agent}} * + k_{sc_{liability}}$$

Agents pay price for their call and internet usage monthly. Price function is depended on the subscribed MNO, subscription type and the age category of the agent. The equation for the price function is as follows:

$$Price = k_{BasePrice_{operator}} + k_{PriceInternet_{operator}} * q_{internet} + k_{PriceCall_{operator}} * q_{call}$$

As stated in the design concepts section, utility from call and internet usage and brand effect have a positive influence on overall utility while price and switching cost effect overall utility negatively. Therefore, overall utility function is formulated as follows:

$$U_{overall} = U_{call} + U_{internet} + BE_{operator} - SC - Price$$

Finally, agents calculate the probabilities of their possible decisions using $U_{overall}$ and logit function at the end of every month. All 6 switching and staying probabilities are calculated as follows.

$$\mathrm{P_i} = \frac{\exp\left(U_{overall_i}\right)}{\sum_{k=0}^{5} \exp\left(\mathrm{U_{overall_k}}\right)}$$

CHAPTER 4

RESULTS

The model is implemented using the simulation and programming tool NetLogo which is described by Blikstein et al. (2010) as one of the most benefitted multi – agent modeling environments. They further claim that it is widely used among scientists from variety of areas including sociology, physics, economics and engineering. Berryman & Angus (2009) indicates that other than NetLogo, there are modeling tools which make performing ABM easier such as Repast, Mason and Swarm. However, NetLogo is advantageous over those as it enables users to define unlimited set of behavioral rules for the agents in the system. It also provides a graphical user interface for visualizing the model and includes useful libraries. User interface of our model is shown in Figure 15.

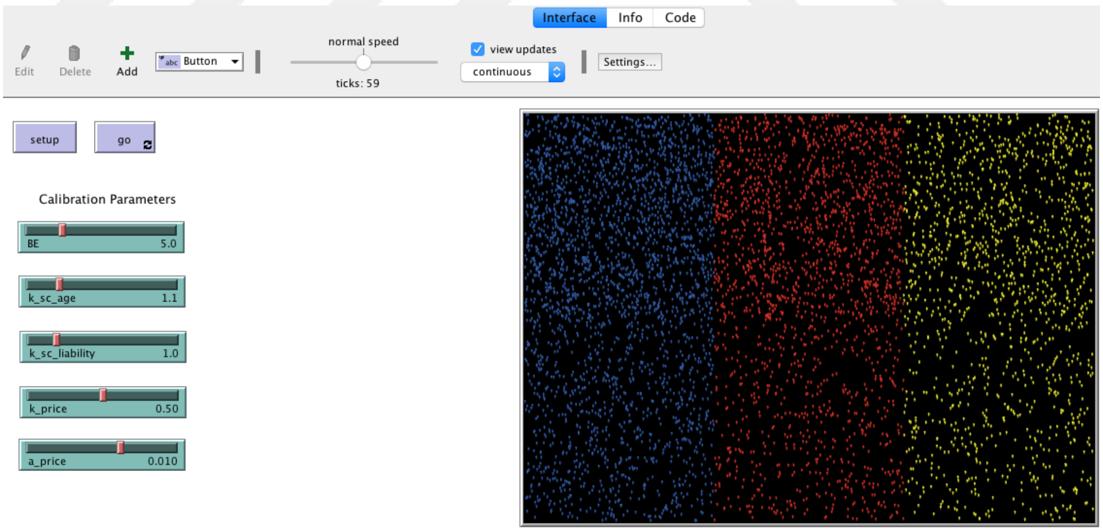

Figure 15. User interface of the model

Parameter initializations are done by pressing the “Setup” button while the “Go” button is responsible for executing monthly processes including operator switching of agents recursively until the predefined maximum simulation tick is reached which equals to 60 for this model each tick representing a month. In the graphical interface, blue agents represent customers of Turkcell, yellow agents show customers of Avea and red agents show customers of Vodafone. As seen in Figure 1, agents are placed according to their subscribed MNOs so that subscribers of Turkcell are on the left, subscribers of Vodafone in the middle and subscribers of Avea on the left of the screen. Subscription type of the agents define their y coordinate as post – paid agents are placed above the origin and pre – paid agents placed below the origin. Sliders enable users to modify calibration parameters. Speed of the simulation can be controlled from the interface as well.

NetLogo includes a tool called Behavior Space for analyzing parameter combinations and their effects on the results. It has the option of replicating combinations more than once as well and it produces an output in .csv format. In this chapter, in order to determine the best parameter sets, calibration analysis is performed in the first place. Afterwards, local and global sensitivity analyses are realized. Uncertainty analysis is applied to the model in the last place.

4.1 Calibration analysis

Railsback & Grimm (2012) point out that calibration process includes running the model number of times for distinct combination of some key parameters and comparing the results with the real-world outputs in order to identify the best values for the most uncertain parameters in the model. As stated in Table 10 previously, there are five calibration parameters in this model namely $k_{sc_{age}}$ and $k_{sc_{liability}}$ denoting the switching cost parameters for age and liability respectively, BE

representing the brand effect parameter, k_{price} and a_{price} effecting the price coefficients.

The reference data, which includes total number of ported numbers and net gain of the MNOs through these ported numbers, for calibrating the parameters are determined from quarterly reports of BTK from the first quarter of 2013 to the last quarter of 2017. Market data for ported numbers and net gain values are given in Figure 16 and Figure 17 respectively.

Figure 16. Number of ported numbers per quarter

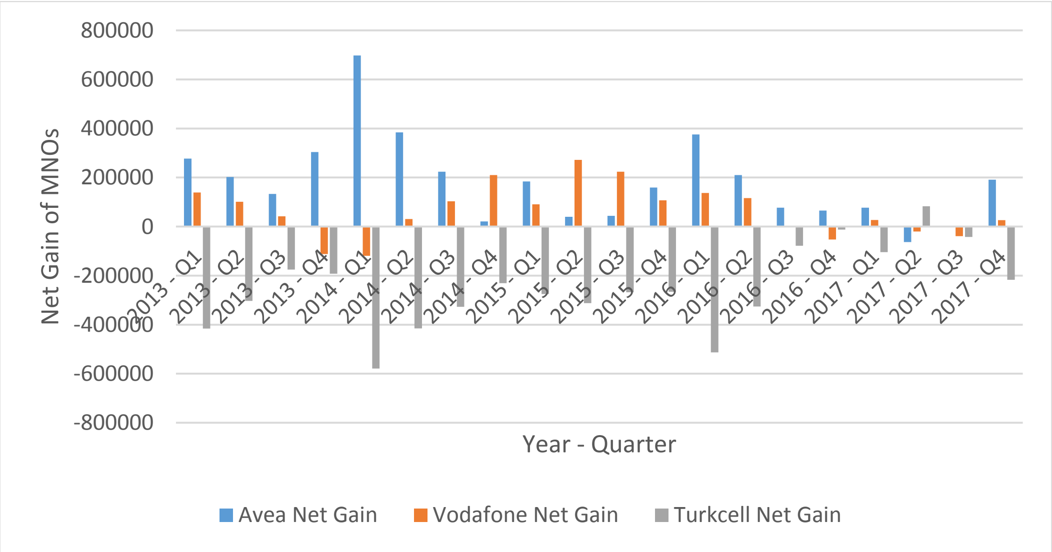

Figure 17. Net gain of MNOs per quarter

As the number of agents in the model is not equal to the actual number of customers in the market, rate of the total ported number and net gain values are considered for calibration criteria. Figure 18 and Figure 19 represent the rate of total ported numbers and net gains of MNOs to the total number of customer in the mobile telecommunications market in respective order.

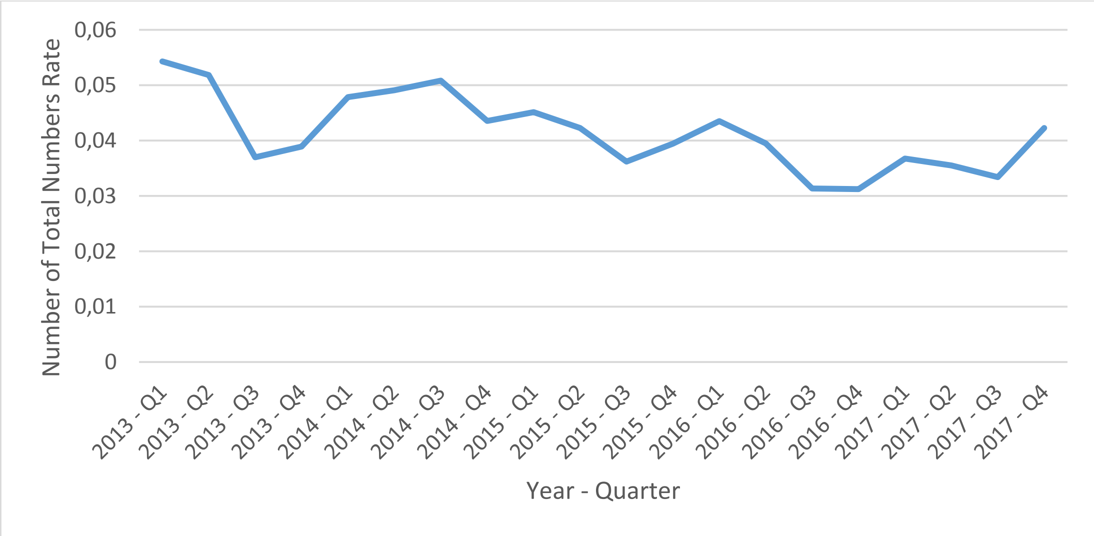

Figure 18. Number of ported numbers rate per quarter

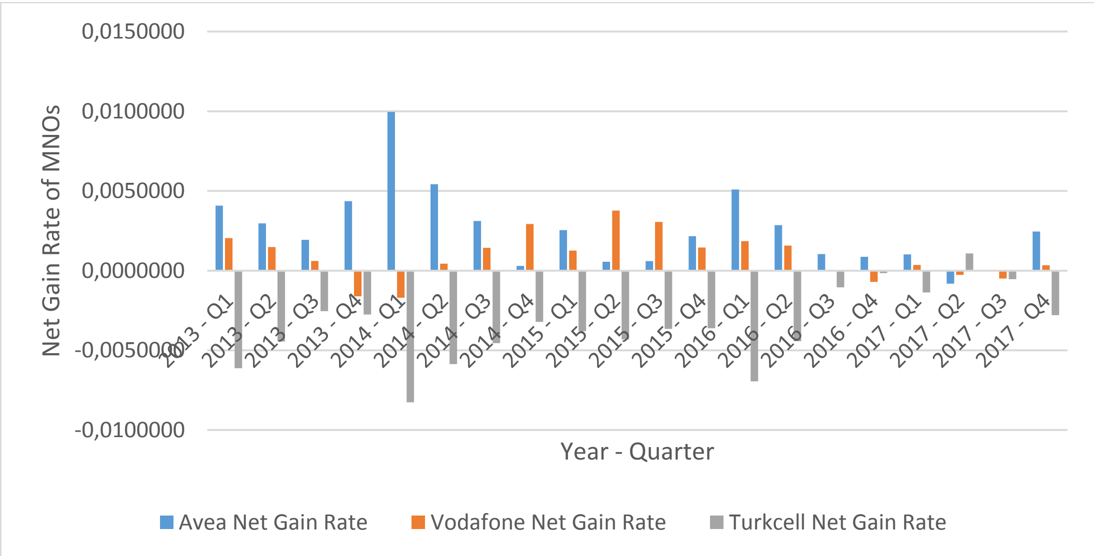

Figure 19. Net gain rate of MNOs per quarter

Calibration criteria is to minimize difference between observed rates and the outputs generated by the model. The formula for the calibration result is given in the following equation where CR stands for calibration result. In the equation, it should be noted that the weight of total number of switch is considered to be bigger than the net customer gain of the MNOs.

$$CR = 0.5 * \left(\left|TotalSwitchRate_{RealData} - TotalSwitchRate_{Output}\right|\right) + 0.5 * \left(\frac{\left|AveaSwitchRate_{RealData} - AveaSwitchRate_{Output}\right|}{3} + \frac{\left|VodafoneSwitchRate_{RealData} - VodafoneSwitchRate_{Output}\right|}{3} + \frac{\left|TurkcellSwitchRate_{RealData} - TurkcellSwitchRate_{Output}\right|}{3}\right)$$

Once the initial consideration of the possible ranges of the calibration parameter values are determined, the model is run by all possible combinations with the help of behavior space tool of NetLogo. Each combination is replicated 10 times and in order to assess the calibration result of the combination, mean value of the repetitions is taken into consideration. Since there are 324 combinations determined, the model is run 3240 times in total including replications for each calibration formula. Ranges of the parameters, the increment values are given in Table 16. The minimum average calibration result of the 10 replications of the best combination is 0.0796.

Table 16. Simulated Calibration Parameter Combinations and Best Fitting Values for The Calibration Formula

Parameter	Minimum Value	Maximum Value	Increment	Best Values
$k_{sc_{age}}$	1	1.3	0.1	1.1
$k_{sc_{liability}}$	1	0.2	1.4	1
k_{price}	0.3	0.5	0.1	0.5
a_{price}	0.005	0.015	0.005	0.01
BE	4	6	1	5

After finding the best combination of parameters, the model is run 50 times and quarterly results are analyzed with the average value, one standard deviation above and one standard deviation below the average and real data for total number of MNO switch rates and net customer gains of each MNO. The results of the analyses made for four different outputs are shown in Figure 20, Figure 21, Figure 22 and Figure 23.

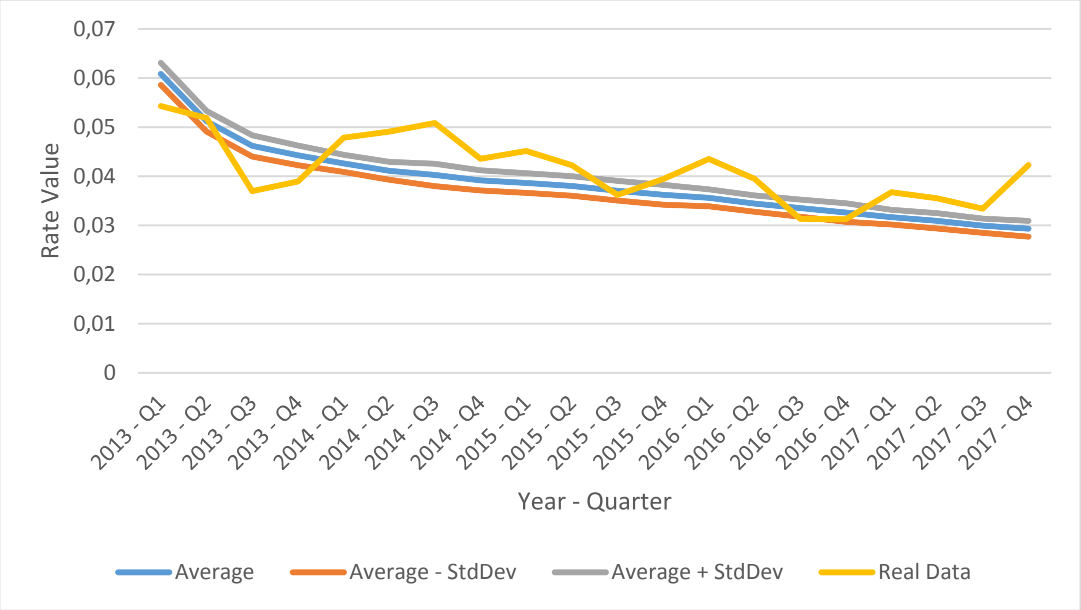

Figure 20. Total number of switch analysis result for calibration parameters

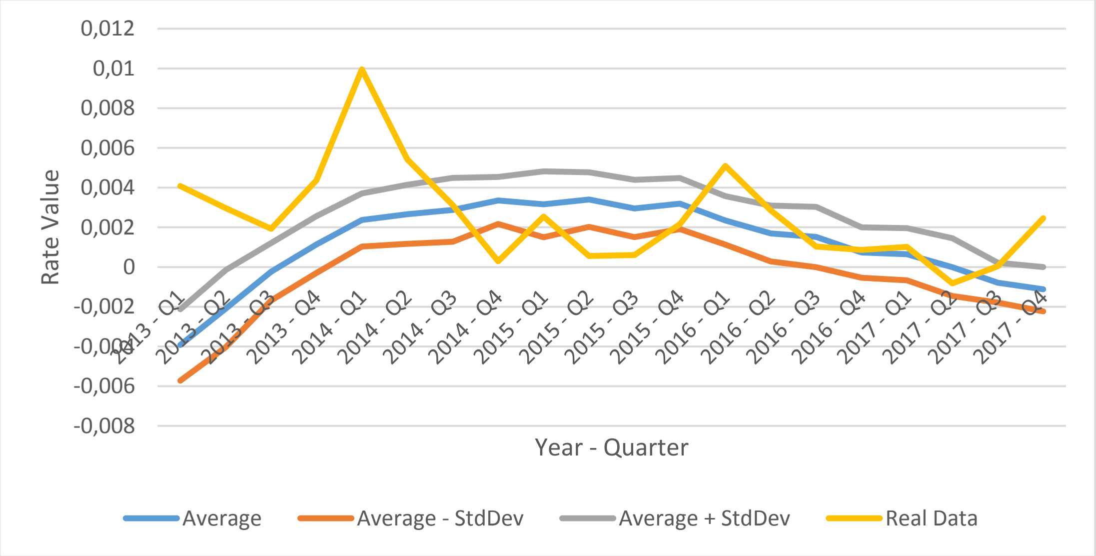

Figure 21. Avea net gain analysis result for calibration parameters

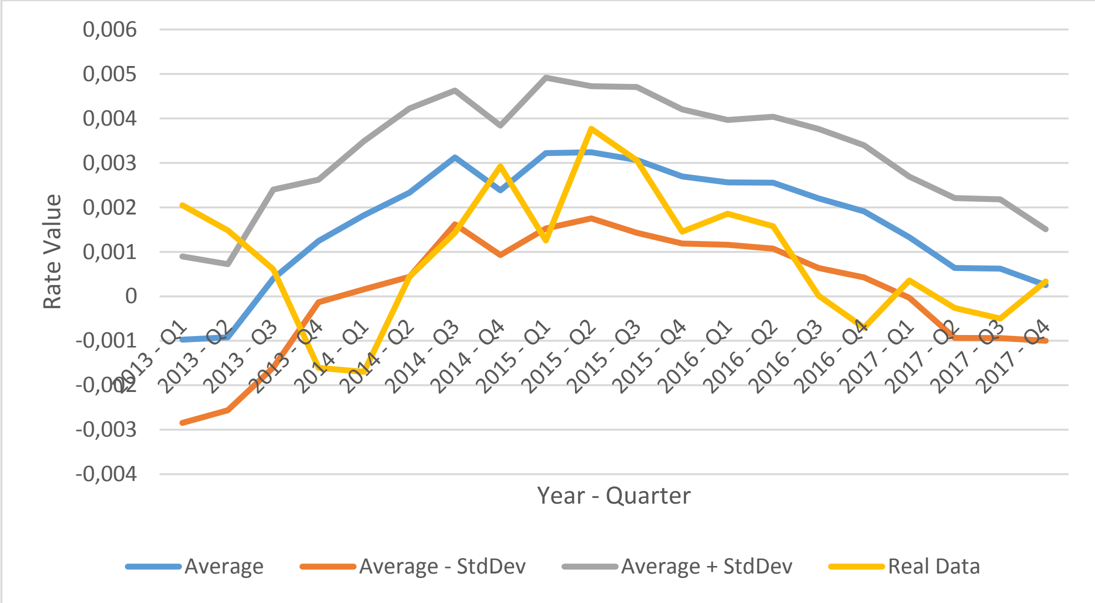

Figure 22. Vodafone net gain analysis result for calibration parameters

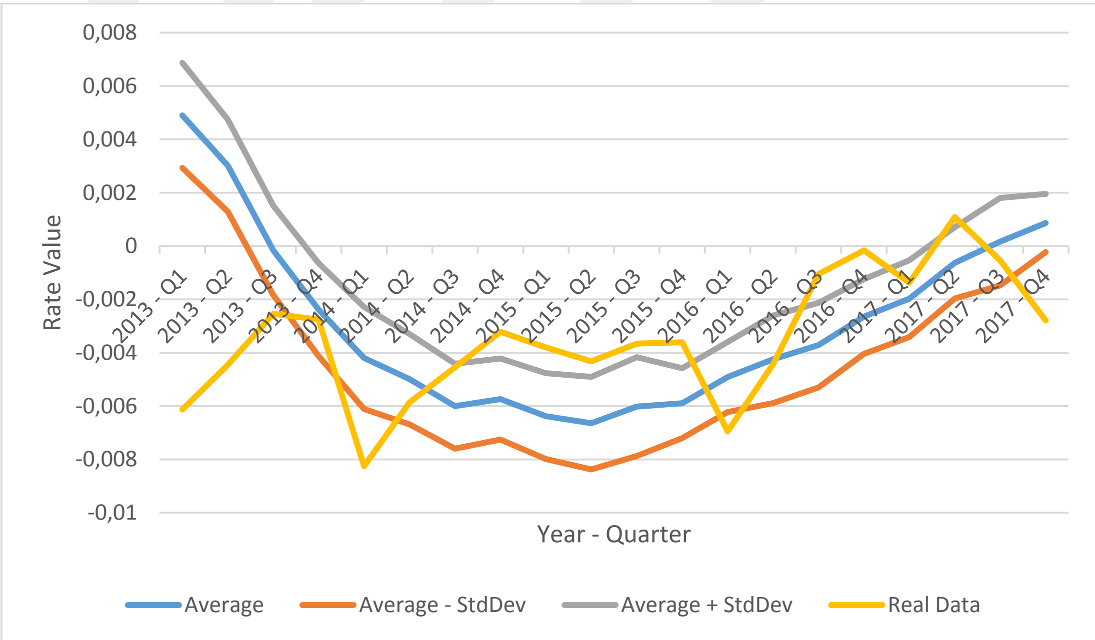

Figure 23. Turkcell net gain analysis result for calibration parameters

Visual inspection of each figure indicates that the model predicts the general trend of total number of MNO switch and the net gain of the MNOs.

4.2 Local sensitivity analysis

Voorn et al. (2013) claim that it is very difficult for researchers to verify and validate ABMs in the model construction phase and sensitivity analysis can be applied for evaluating such systems. According to Railsback & Grimm (2012), the purpose of local sensitivity analysis is to identify the sensitivity of the model outputs to a selected parameter which varied within a small range while the other parameters stay the same. The formula for local sensitivity as in the way used in this model is presented as follows.

$$S = \frac{\frac{\frac{\Delta O_{+}}{O}}{\frac{\Delta P_{+}}{P}} + \frac{\frac{\Delta O_{-}}{O}}{\frac{\Delta P_{-}}{P}}}{2}$$

where S denoting the sensitivity result. ΔO_{+} and ΔO_{-} represent the difference in the outputs for varying parameters as follows.

$$\Delta O_{+} = O_{(P+h_1)} - O_{(P)}$$

$$\Delta O_{-} = O_{(P)} - O_{(P-h_2)}$$

ΔP_{+} equals to h_1 since it represents the difference between P and the incremented parameter, $P + h_1$. Similarly, ΔP_{-} equals to h_2 as it shows the difference between P and the decremented parameter, $P - h_2$. Equations for ΔP_{+} and ΔP_{-} are presented below.

$$\Delta P_{+} = (P + h_1) - P$$

$$\Delta P_{-} = (P - h_2) - P$$

Local sensitivity analysis is applied to four parameters and their respective outputs which are $k_{sc_{age}}$ and total number of ported numbers, base price parameter for Turkcell and total net gain of Turkcell, base price parameter for Avea and total net gain of Avea and base price parameter for Vodafone and total net gain of Vodafone. Both h_1 and h_2 are determined to be 1% of the analyzed parameter since the range should be small for local sensitivity. Results of the local sensitivity analysis for the parameter $k_{sc_{age}}$ and total number of ported numbers as the output is presented in Table 17.

Table 17. Sensitivity Analysis of Age Coefficient of The Switching Cost

Parameter	Value		
$k_{sc_{age}}$	1.089	1.1	1.111
Rate of total number of ported numbers	0.0428	0.0415	0.0399
Sensitivity Result	-3.5		

As expected, sensitivity result is calculated as a negative since the switching cost and number of ported numbers are inversely correlated as it negatively effects the overall utility function for the cases include switching. The result shows that age coefficient of the switching cost is a highly effective parameter for changing total number of switching in the simulation period since 1% change in the parameter results -3.5% change in the inspected output.

Local sensitivity analysis is also applied to the base price parameter of the MNOs and their total net gain rate throughout the simulation where the first calibration parameters set is considered. Price parameter is selected for the analysis since it is one of the most important factors for customers when they decide to switch between MNOs. It also helps us to understand how price sensitive the customers of each MNO are. Results of the local sensitivity analysis of base price of Avea, Vodafone and Turkcell are shown in Table 18, Table 19 and Table 20 respectively.

Table 18. Sensitivity Analysis of Base Price Parameter for Avea

Parameter	Value		
$k_{baseprice_{avea}}$	9.99	10	10.1
Rate of total net gain of Avea	0.148	0.137	0.107
Sensitivity Result	-15		

Table 19. Sensitivity Analysis of Base Price Parameter for Vodafone

Parameter	Value		
$k_{baseprice_{vodafone}}$	9.99	10	10.1
Rate of total net gain of Vodafone	0.196	0.186	0.154
Sensitivity Result	-11.3		

Table 20. Sensitivity Analysis of Base Price Parameter for Turkcell

Parameter	Value		
$k_{baseprice_{turkcell}}$	9.99	10	10.1
Rate of total net gain of Turkcell	-0.279	-0.302	-0.333
Sensitivity Result	-8.9		

Local sensitivity analysis applied to base price parameters show us that total net gain rates are significantly affected by the price for each MNO. As expected, sensitivity results are obtained negative for all the MNOs since the price effects negatively the overall utility function for all cases. It can be deduced from the results that customers of Turkcell are the least price sensitive of all operators while the customers of Avea are the most price sensitive and customers of Vodafone are situated in the middle.

4.3 Global sensitivity analysis

As local sensitivity analysis has some drawbacks such as presumption of linearity, global sensitivity analysis become necessary to apply since it takes into account of all the variational change in parameters. Unlike local sensitivity analysis, in global sensitivity, parameters vary in a larger range in order to have a broader understanding of how the parameter and the output are correlated.

In this model, parameters are varied around 30% of their values with 7 values in total having the same interval with subsequent ones. Similar to local sensitivity analysis, $k_{sc_{age}}$ parameter of switching cost function and base price parameters for each MNO selected as global sensitivity parameters while the analyzed outputs are total number of ported numbers rate and total net customer gain rate of the MNOs. The results obtained after the global sensitivity analysis are presented in Figure 24, Figure 25, Figure 26 and Figure 27.

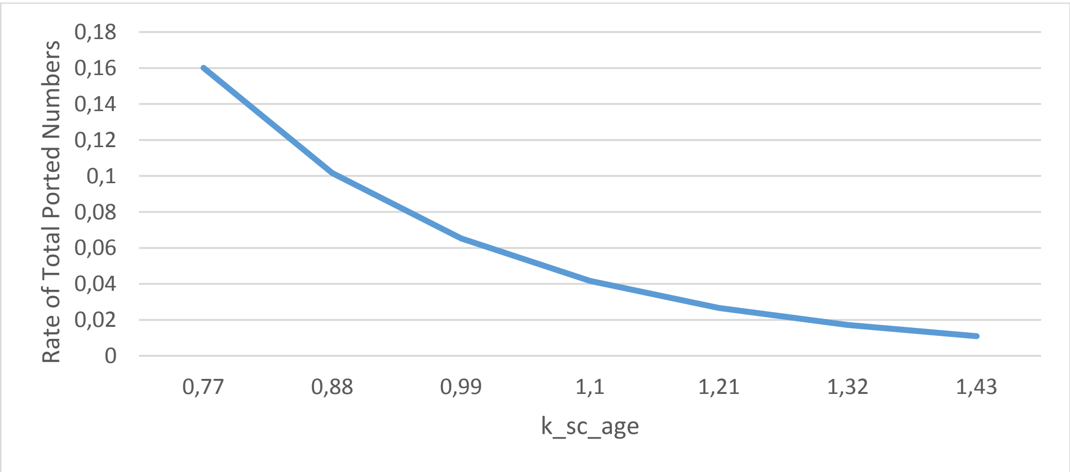

Figure 24. Global sensitivity analysis of k_sc_age and number of ported numbers

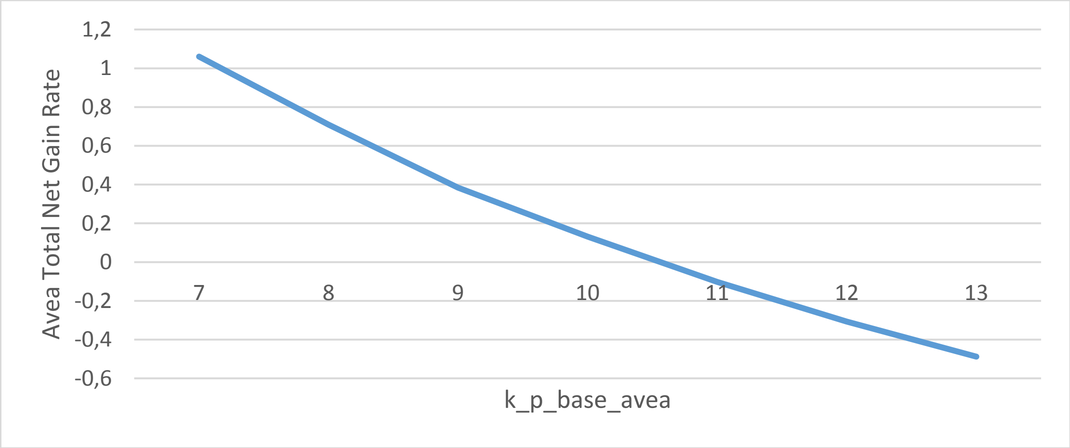

Figure 25. Global sensitivity analysis of Avea base price and Avea net gain

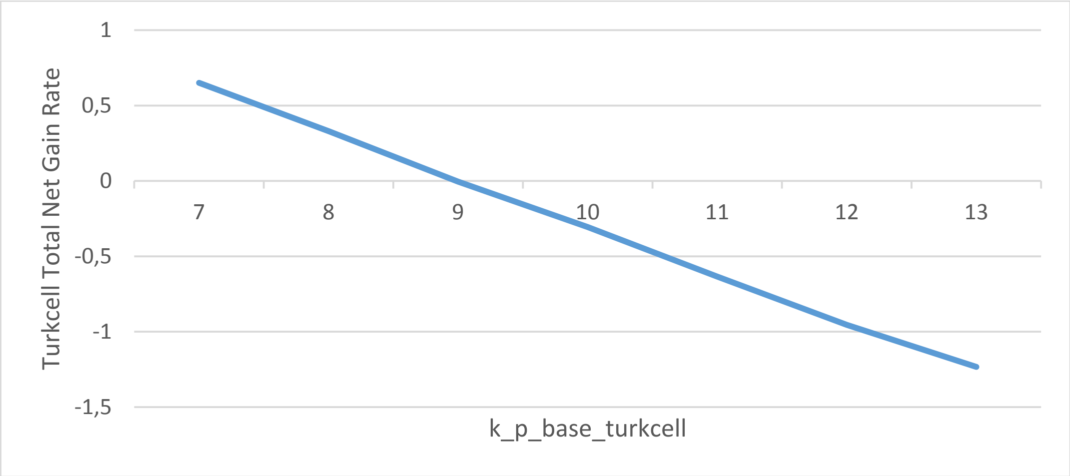

Figure 26. Global sensitivity analysis of Turkcell base price and Turkcell net gain

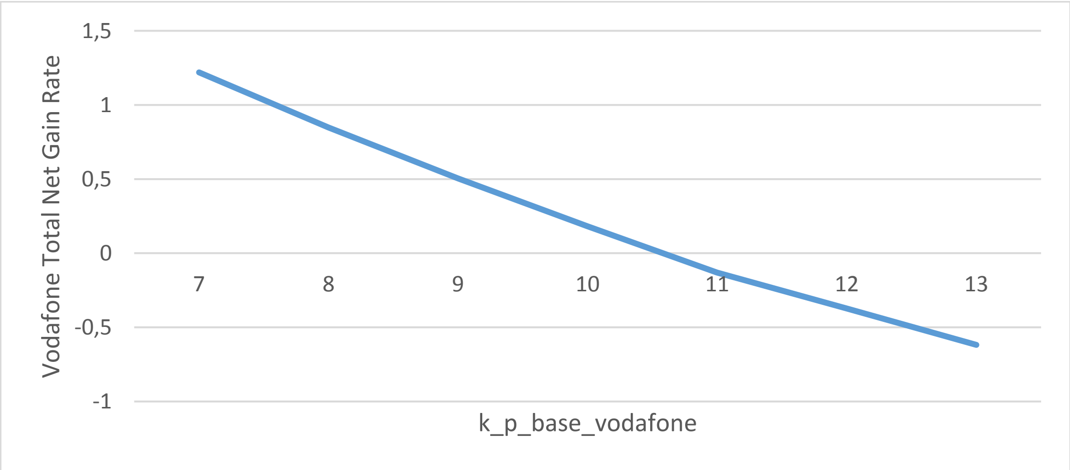

Figure 27. Global sensitivity analysis of Vodafone base price and Vodafone net gain

Global analysis of these four parameters and their respective outputs show us that there is a consisted relationship between them when we vary the parameters in a bigger range than in local sensitivity analysis. It can be discussed that $k_{sc_{age}}$ parameter and the total number of switch are negatively related when the range of the $k_{sc_{age}}$ is determined as $[0.77,\ 1.43]$ with increments of 0.11 which is 10% of $k_{sc_{age}}$ as illustrated in Figure 24. Similarly, the base price parameters of MNOs and their net gains are negatively correlated as well. In the analysis all three base price parameters are ranged in [7,13] with increments of 1 as presented in Figure 25, Figure 26 and Figure 27 for Avea, Turkcell and Vodafone respectively. The results of global sensitivity analysis also support the outputs of local sensitivity analysis.

4.4 Uncertainty analysis

Railsback & Grimm (2012) defines uncertainty analysis as a method used for comprehend how uncertainty of parameters effect the results of the simulation. Ligmann-Zielinska et al. (2014) indicate that uncertainty in ABMs has to be addressed since they are constitutionally stochastic. Unlike global sensitivity analysis, values of the parameters are distributed randomly in uncertainty analysis. For this model, age parameter of the switching cost and brand effect parameter, namely $k_{sc_{age}}$ and BE, are chosen and they are distributed normally having the mean of the parameter's calibrated value and the standard deviation of 10% of their respective values. The simulation is run 1000 times for each parameter and the output which is analyzed for both of the parameters is chosen as the rate of total number of switch in the simulation period. Figure 28 and Figure 29 represent uncertainty analysis results for $k_{sc_{age}}$ and BE respectively.

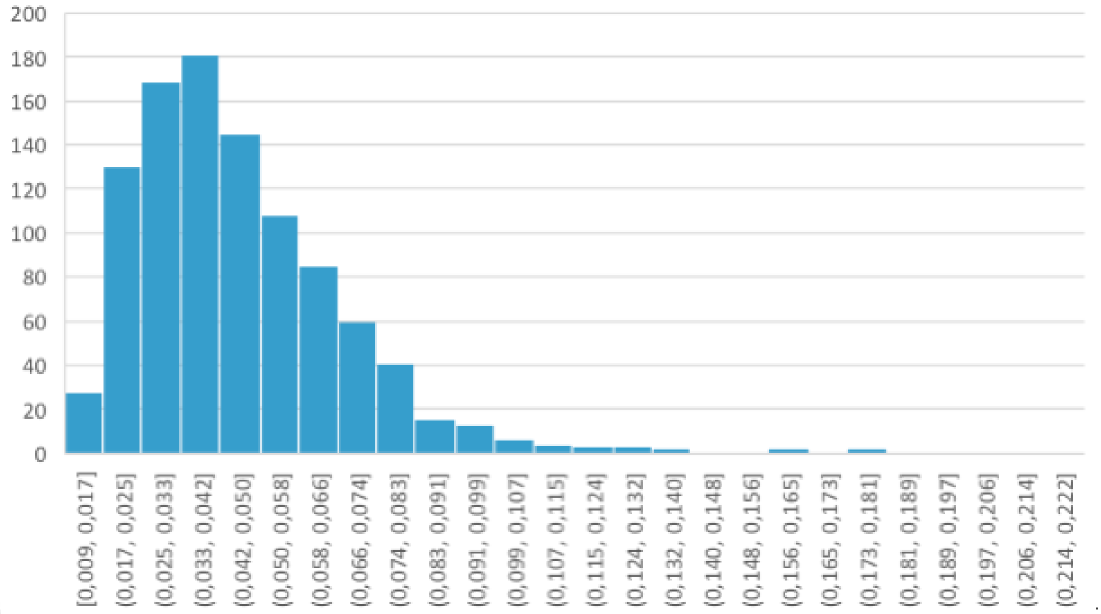

Figure 28. Uncertainty analysis of k_sc_age parameter

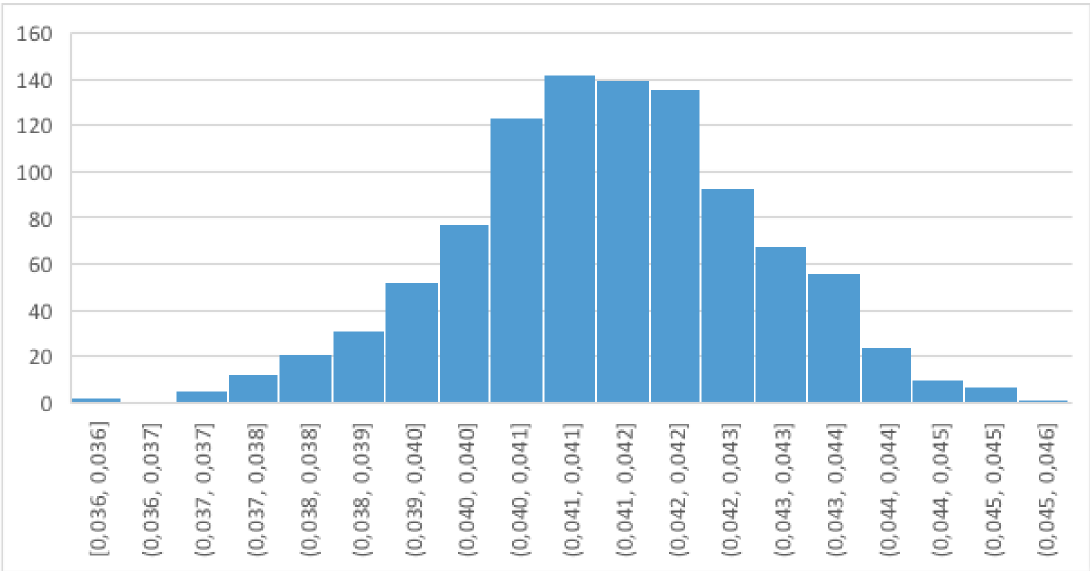

Figure 29. Uncertainty analysis of brand effect parameter

Examination of these figures show that the output of the model - total number of operator switch is not unstable when we randomly distribute $k_{sc_{age}}$ and BE individually.

CHAPTER 5

CONCLUSION

In this research, Turkish mobile telecommunications market is modelled with Agent-Based approach in order to analyze operator switching behavior among customers and the key factors effecting this behavior. As the market is getting more complex with increasing number of customers and newly introduced technological advancements in the field of telecommunications, ABM is chosen as the modeling technique since it is flexible and it allows modeling with social parameters which are rapidly changing. It also allows us to work with heterogenous agents. Background of ABM and its applications to telecommunications markets is given in detail as well.

The constructed model is outlined using ODD protocol as it provides a common framework for ABMs and makes it easier to replicate models. Agent and environment parameters, agent behavior formulations and the flow chart of the model are also represented. Real – world market data source used in this research is taken from quarterly reports of BTK, from the beginning of 2013 to the end of 2017. NetLogo 6.0.3 is used as the simulation and programming tool for executing the model as it provides analysis tools specialized for ABMs and a GUI for visualizing the events.

Calibration analysis applied to the model in the first place in order to get the best parameter set according to the calibration criteria which is based on total number of MNO switch and total net gain of the operators. The results show that the prediction of the model gets better after the initial phase for both total number of switches and total net gains. Local sensitivity analysis is performed subsequently for age parameter of the switching cost and base price parameters of each MNO. From the analysis it can be claimed that the market, in terms of MNO switching behavior, is highly sensitive to the monthly price the customers pay. Turkcell has the least price sensitive customers while the customers of Avea are the most price sensitive of all. It can be discussed that brand effect and prices are negatively related and MNOs can take this finding into consideration trying to increase their brand effects in order to have less price sensitive customers. The results of the global sensitivity analysis also supported the local sensitivity results as the relationship between selected parameters and outputs is similar when the range of the parameters is increased. Uncertainty analysis is applied in the last place for age parameter of the switching cost and brand effect parameter. The results of this analysis show that the outputs are stable when we normally distribute these parameters.

Finally, future advancements to the model may include a simulation-based game theoretical framework as the number of MNO switch is not only depended on strategical moves of the currently analyzed MNO but actions of the other MNOs as well. In this way, operators can assess the strategies of their rivals and make decisions accordingly. Apart from this, conjoint analysis can be applied to the model in order to obtain more accurate values for behavioral parameters shaping the overall utility function.

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