

Kanellos, Nikolaos; Katsianis, Dimitrios; Varoutas, Dimitrios

Conference Paper

Forecasting a telecommunications provider's market share

31st European Conference of the International Telecommunications Society (ITS): "Reining in Digital Platforms? Challenging monopolies, promoting competition and developing regulatory regimes", Gothenburg, Sweden, 20th - 21st June 2022

Provided in Cooperation with:

International Telecommunications Society (ITS)

Suggested Citation: Kanellos, Nikolaos; Katsianis, Dimitrios; Varoutas, Dimitrios (2022) : Forecasting a telecommunications provider's market share, 31st European Conference of the International Telecommunications Society (ITS): "Reining in Digital Platforms? Challenging monopolies, promoting competition and developing regulatory regimes", Gothenburg, Sweden, 20th - 21st June 2022, International Telecommunications Society (ITS), Calgary

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Forecasting a telecommunications provider's market share

Nikolaos Kanellos
Dept. of Informatics and
Telecommunications
University of Athens, UoA
Athens, Greece
kanetza@di.uoa.gr

Dimitrios Katsianis
Dept. of Informatics and
Telecommunications
University of Athens, UoA
Athens, Greece
dkats@di.uoa.gr

Dimitrios Varoutas
Dept. of Informatics and
Telecommunications
University of Athens, UoA
Athens, Greece
DVaroutas@di.uoa.gr

Abstract

Telecommunications providers' market share risks stem from uncertainties due to overall market performance and competition strategies adopted by providers. In this paper, a framework that allows risk-adjusted forecasting of a provider's market share is presented. Two different stochastic processes are deployed to model the effects of churn and attraction strategies, as well as market performance. Impact results are obtained through the application of Monte Carlo simulation. The proposed framework was verified and validated with the use of a typical test scenario. Application findings are consistent with relative churn and attraction management literature, indicating a best performer advantage and a minimum systematic risk impact on a provider's market share expectations. The proposed framework can help telecommunication providers to understand and adjust their strategies regarding churn management and new customer attraction and can be extended to include market structure analysis and forecasts as well.

Keywords: Telecommunications, market share analysis, risk analysis, Markov decision process, Ito process, Monte Carlo Simulation

1. Introduction

Market share refers to the portion or percentage of a market earned by a company or an organization. It is a key indicator of the relative competitiveness of the company's products or services. Moreover, market share increases can allow a company to achieve greater scale with its operations and improve profitability.

Changes in a company's market share may be attributed to overall market performance and churn (Farris et al. 2015). Churn occurs when customers stop buying products or using services from a company. Consequently, since their ability to impact market performance is limited, companies focus on developing churn management strategies.

The above hold true in the telecommunications' sector. A provider's market share relies upon market performance and telecommunications' churn. The latter represents a situation when a subscriber decides to leave a service provider and switches to another operator (Chouiekh and Haj, 2020). As a result, providers compete to acquire new subscribers and retain existing ones, considering that the costs of retaining the existing customer are usually much lower than attracting a new customer (Kim et al. 2020). The success of their strategies depends not only on the provider's performance but also on the performance of the competitor firms. Therefore, a provider may fail and exit the market, even if the market overperforms (Mattison, 2006).

The most proposed models for competition modeling and market share forecasting in the telecommunications' sector involve the use of Markov chains and Markov decision processes (MDPs). These models aim to study customer loyalty and to forecast the brands, products, or services that a customer is likely to purchase next. Thus, as aggregation of individual customer choices, market shares of providers and their competitors can also be studied using similar approach. Furthermore, they have been extended to include the telecommunications' market dynamics, such as the diffusion patterns exhibited by novel telecommunication services etc.

Despite the Markov models use for telecommunication competition modeling, up to the authors' knowledge, no complete framework has been proposed that enables the assessment of demand risks. This constitutes a gap in the related literature since the resulting long-run forecasts do not include the effects of uncertainties caused by actions, decisions and policies undertaken by the underling market competition regime.

Consequently, the purpose of this study was to propose a framework that allows risk-adjusted forecasting of a provider's market share in the long-run. The proposed framework utilizes a Markov decision process (MDP) to model the effects of churn management strategies undertaken by competitor providers. These providers are allowed to compete over the limited subscribers resulting from an uncertain market performance, simulated with the use of a calibrated Ito stochastic process. Furthermore, if required, special decision variables and restrictions may be inserted to enable market structure analysis and forecasting. Finally, the impact of risks and uncertainties originating from competition strategies and overall market performance on a provider's market share and/or market structure expectations is explained through Monte Carlo Simulation.

The above framework was verified and validated through a test scenario. This scenario involved a typical new service market in a growing mobile telecommunications' industry. Application results are consistent with relative churn and attraction management literature and databases, indicating a best performer advantage and a minimum systematic risk impact on a provider's market share expectations.

Consequently, the proposed framework can help telecommunication providers to understand and adjust their strategies regarding churn management and new customer attraction, as well as serve as an aid for understanding competitive interactions in the market.

The rest of this paper is organized as follows. Section 2 provides a brief literature review over the use of Markov models for market share forecasting in the telecommunications' sector. Sector 3 presents the proposed framework formulation. Framework verification and validation is presented in Section 4. Finally, Section 5 concludes the study.

2. Literature Review

Academic research on market share models has spanned over the years, with Modeling approaches varying, among others, from the use of simulation-based methods (Fok and Franses, 2001), attraction models (Kumar, 1994) to neural networks and genetic algorithms (Gruca and Klenz, 1998).

The use of Markov models in market share analysis dates back to the work of Deming and Glaser (1968). In their study they present a Markovian analysis of the life of newspaper subscriptions.

In the telecommunications' sector, market share modeling with the use of Markov models was introduced with Sokele and Moutinho (2006). Their work indicated that the transition matrix of time-homogeneous Markov chain has descriptive features and can be linked with explanatory marketing variables. Their analysis was based on examples from the telecommunications' industry.

In Sokele et al. (2009), a diffusion growth model was included in the Markov formulation to forecast changes in market share according to phases in the product life cycles. Again, the analysis was based on examples from the telecommunications' industry.

Datong (2011), Yang and Sha (2011) and Chan et al. (2012) utilize Markov chains to model market shares of mobile operators. Chan et al. (2012) also propose that mobile subscriptions offer a more contemporary example to introduce students to Markov chains.

In Chan et al. (2013), a non-homogeneous Markov model was applied to forecast market shares of all competitors, using non-stationary transition probability matrices, which could be modified to reflect consequences due to actions, e.g. marketing activities taken by providers.

Chan (2015) presented four mathematical models for the same market share problem based on different underlying assumptions. The aim of this study is to provide guidance over forecasting model selection based on the underlying characteristics and nature of the problem. This was illustrated through the application of these models to the same subscribers switching problem between providers in the telecommunications industry.

Lastly, Vijayaragunathan and John (2022) explored the consumer brand preferences while purchasing SIM cards from service providers, using the Markov Prediction Chain model. They found that the public sector players lose to the private sector players.

In all these previous studies, the Markov chain model was used to investigate the movements of a group of buyers among a number of sellers, and market shares as proportions are used in the state vectors.

The proposed framework builds upon the works of Chan et al. (2013) and Sokele et al. (2009) to model the telecommunications' market dynamics and introduces the use of risk assessment tools to allow a risk-adjusted forecast of a provider's market share in the long-run.

3. Framework Formulation

The market share (the number of subscribers) held by a telecommunications provider is a product of its ability to attract new and retain existing subscriptions, despite the overall telecommunications' market performance. Consequently, over a specific time period, the number of subscribers to a provider at the end of this period can be estimated following Eq.1.

$$SB_t = SB_{t-1} + (C_t^p + C_t^n) + (M_t^p + M_t^n) \quad (1)$$

where:

- SB_t : The number of subscribers to the provider at the end of the time period
- SB_{t-1} : The number of subscribers to the provider at the beginning of the time period
- C_t^p : The number of attracted subscribers originating from competition (positive churn) over the time period
- C_t^n : The number of subscribers leaving the provider for competition (negative churn) over the time period

- M_t^p : The number of attracted new-to-market subscriptions over the time period
- M_t^n : The number of subscribers leaving the market over the time period

Parameters C_t^p and C_t^n together express the effects of subscriber churn on the provider's market share, whereas parameters M_t^p and M_t^n together express the effects of overall market performance on the provider's subscriber base. Similarly, parameters C_t^p and M_t^p together express the incoming subscribers, whereas C_t^n and M_t^n together express the customers leaving the provider.

Following the aforementioned approach (Eq.1) of the time-evolution of a provider's market share, the principal risk of poor market share performance can be attributed to:

- a. The poor performance of the provider's churn management strategies.
- b. The superior performance of the competitors' churn management strategies.
- c. The overall performance of the market.

At any time step, these risk sources create flows of subscribers that impact the providers' market share. To understand this impact, in the proposed framework two different stochastic processes are deployed to model the effects of churn and attraction strategies and market performance on long run market share. Results are obtained through the application of Monte Carlo simulation.

A. Churn Modeling

To model the effects of the competitive churn management strategies on the provider's market share, a Markov decision process (MDP), similar to the one presented in Chan et al. (2013), was selected.

An MDP is a discrete time stochastic control process. At each time step, a set of actions is allowed for each state. The decision maker chooses an action from a set of allowable actions and the process moves randomly from one state to a new state, giving the decision maker a reward accordingly. When there is no action applied, an MDP becomes a Markov chain (MC) with a constant transition probability matrix.

In the proposed framework, MDP is used to model the providers' market share and to include actions, decisions and policies, and rewards relating to their churn management strategies. The MDP's state space consists of all active providers. At each time step, a subscriber may obtain service from any one of the providers. Moreover, each provider is a decision maker, and has its own set of allowable actions – churn managing strategies. Providers make decisions independently. At each time step, each provider chooses to take or not to take any competitive churn management action. The cumulative rewards of the application of all competitive strategies can be seen as changes in the providers' market share at the end of the time step (the beginning of the next time step).

Given the above, at each time step, a provider's outgoing subscriber number due to churn is simulated. This change in the provider's market share is the cumulative result of the application of the providers' competitive churn management actions at the time period under study. Since this flow of subscribers is attributed to churn, they are then divided to the competitive providers, accounting for their successfully attracted customers.

From a provider's perspective, this flow of subscribers due to churn during a time period is described by Eq.2:

$$X_t = X_{t-1} - OutX + InX \quad (2)$$

where:

- X_t : The provider's market share at the end of the time step
- X_{t-1} : The provider's market share at the beginning of the time step
- $OutX$: The outgoing number of subscribers due to churn
- InX : The incoming subscribers due to churn.

To enable long run forecasting of churn effects, parameter $OutX$ in Eq.2 above was simulated as a bounded variable, whose value is selected in a random way, e.g. the number of subscribers follows a flat uniform or normal distribution that draws values from a defined set. This approach is consistent with the findings of various market reports [e.g. Kaur (2017) and Koptuyug (2022)]. Similarly, InX is simulated as the sum of the percentages of the outgoing subscribers from competition that become incoming subscribers for the provider under study. Again, these percentages are defined in a bounded random way. The aforementioned boundaries may be selected as time-homogenous or not for the forecasting period, based on the study hypotheses.

Consequently, following the notation of an MDP model presented in Chan et al. (2013), the proposed approach constitutes an MDP model with randomly varying transition probabilities throughout the forecasted period – each element of the transition matrix is allowed to vary across time steps in a bounded random way.

B. Market Performance Modeling and Customer Attraction

Unlike the works of Sokele et al. (2009) and Chan (2015), where a diffusion growth model was included in the Markov formulation to forecast changes in market share with the use of a growth matrix, in the proposed framework, the overall market is considered equal to the sum of the providers' specific market share.

$$y(t) = y_1(t) + y_2(t) + \dots + y_i(t) \quad (3)$$

where:

- $y(t)$: the total number of all active subscribers of all providers available at time t .
- $y_i(t)$: the number of active subscribers of the i -th provider.

The proposed methodology was inspired by the stock-flow consistent macroeconomic Modeling (Godley and Lavoie, 2007). Stock-flow consistent Modeling, different groups compete over limited resources, with demand functions subjected to "adding up constraints".

Under this approach, changes in the market performance are directly reflected on the providers' subscriber base. This process involves flows of new market entrants and subscribers leaving the market that occur simultaneously but not in correlation with churn flows.

With the framework's goal being the impact of subscribers' flows to the providers' market share, a top-down modeling of this process was selected; modeling should consider the entire market and changes should then be diffused to providers.

Given the above, the calibrated Ito stochastic process approach presented in Kanellos et al. (2021) was selected to model the overall market performance. This approach integrates the traditional diffusion of innovations theory with stochastic processes, thus enabling the introduction of diffusion uncertainty in long run diffusion forecasting.

The proposed calibrated Ito stochastic process is presented in Eq.4:

$$dx = \mu(t)dt + b(x, t)dz \quad (4)$$

where:

- dz is the increment of a Wiener process
- The coefficient $\mu(t)$ corresponds to the calibrated diffusion growth rate, given by Eq.5
- Parameter $b(x, t)$ corresponds to volatility exhibited by the data, as a result of uncertainty.

$$\mu(t) = \frac{\sum_0^t N(t) - \sum_0^{t-1} N(t-1)}{\sum_0^{t-1} N(t-1)} = \frac{N(t)}{\sum_0^{t-1} N(t-1)} \quad (5)$$

It is noted that in the absence of volatility [$b(x, t) = 0$], the results of (4) converge to the S-shaped diffusion model that best-fits the market data.

Subsequently, following the estimation of the market performance at each time step, changes in the total number of subscribers in the market are divided across providers. Again, a bounded random methodology is proposed. In this case, the boundaries reflect the level of attraction achieved by each provider, from the new market entrants' perspective. On the contrary, since subscribers' market exit is mostly affected by external market factors, rather than provider actions, it is considered that these factors are incorporated in the volatility coefficient of the calibrated Ito stochastic process describing the overall market performance. Therefore, subscriber market exit impacts providers through the bounded random subscriber division process used for market changes.

C. Impact Analysis

Given the subscribers' flow Modeling in the telecommunications' market provided above, to generate possible demand forecasts, Monte Carlo Simulation is deployed.

In the proposed modeling, the providers' market share values are estimated together at every time step. Thus, Monte Carlo outputs include the probabilistic distribution of the expected market share of all active providers at the time period under evaluation. It is noted that even though there is no constrain for the forecast period, the larger this period, the higher the expected data deviations due to the underlying uncertainty.

Moreover, the sensitivity analysis available through Monte Carlo simulation may be used to identify key parameters that affect significantly, both positively and negatively, the forecasted market share. Thus, providers are able to precisely identify actions that achieve the most beneficial outcome, based on their goals.

Last, besides the generation of future diffusion forecasts, Monte Carlo simulation may be used to estimate the risk inherent to the providers' market share evolution process. The calculated probabilistic distribution constitutes a risk assessment of the forecasted providers' market share under study. Results may be compared to various levels of risk tolerance.

The above can help telecommunication providers to adjust their strategies regarding churn management and new customer attraction. This concludes the proposed framework.

D. Extensions

The following extensions – uses may be considered for the proposed framework:

i. Short term Competitor Interaction Analysis

For already established markets, where time series data regarding providers' performance is available, the opposite process may be applied.

Focusing on a specific time step, the providers' market share data may be used to identify the value of the modeling parameters. This may be performed through data fitting practices.

Under this approach, a provider may identify the actual impact that its strategies had on competition, as well as to review its tolerances against competition.

ii. Market Structure Modeling and Forecasting

The proposed framework is based on the dynamic modeling of providers' interactions. These interactions include market entry and/or exit of a provider.

At any time step, a decision variable may be used to model market entry of a new provider. This decision variable may be case specific, e.g. linked to the overall market performance, or can be arbitrary. Multiple entries are also an option.

Furthermore, restrictions may be imposed that generate a provider's exit, e.g. if the market share of the provider goes below a threshold value. This may apply to all active providers in the market, thus enabling multiple exits.

The decision variables and restrictions have to be modeled according to the user's requirements – views of these changes to properly simulate the additional subscriber flows that occur at those events.

Following this approach, the proposed framework may be used for long-run market structure modeling and forecasting in conjunction with market share analysis.

4. Framework Verification & Validation

To confirm that the proposed framework meets its specifications and intended use, verification and validation activities were considered.

A. Framework Verification

Based on the framework's conceptual description, verification requirements were twofold: (a) inputs should be consistent with actual market data and (b) outputs should allow risk assessment to be performed for a provider's market share.

The use of random bounded distributions to model the effects of the customer attraction and churn management strategies is consistent with the relating literature regarding a provider's churn and attraction estimation, e.g. Melian et al. (2022). These parameters are usually provided as time series data, thus enabling tracking of changes and distribution fitting (Koptug, 2022). Monte Carlo simulation provides the flexibility to use these uncertain variables as is, rather than static single average numbers, to perform forecasts.

Moreover, Monte Carlo simulation produces distributions of possible outcome values. In this case, these distributions visualize a forecast's full range of possible outcomes, which constitutes a risk-adjusted forecast of a provider's market share. The accuracy of the results depends on the number of the realizations performed.

In addition, the underlying sensitivity analysis pinpoints the simulation parameters' contribution to simulation results. Therefore, through this analysis, a provider may identify key parameters that have a significant impact on its expected market share.

The above verify the framework's correct operation. Providers are able to use their own estimations/views to perform long-run market share risk-adjusted forecasts.

B. Framework Validation

To ensure that the proposed framework meets the intended functionality and user needs, a validation plan was drawn up, consisting of validation requirements and a test scenario.

i. Validation Requirements

Intuition suggests that the provider with the with the most effective new customer attraction and churn management strategies has the higher probability to capture the higher market share among competitors. In addition, providers that have similar strategies in terms of efficiency should capture a similar market share.

Furthermore, the findings of churn prediction studies, e.g. Kim et al. (2020), were considered. According to these studies, churn management strategies have a high impact on a provider's performance, whereas overall market performance and new customer attraction have a significantly lower affect. Hence, they suggest that providers should focus their efforts on customer service processes.

The proposed framework should conform to the aforementioned intuition and research findings, which constitute the validation requirements.

ii. Test Scenario

To validate the framework's usability, the case of three telecommunication providers competing in a new service market in a growing mobile telecommunications' industry is considered. These providers make decisions and formulate their strategies on an annual basis. Additionally, a period of 15-years was selected for study, which is not an extreme lifespan in the telecommunications' sector.

The proposed scenario was based on the mobile telecommunications' market in Greece. In short, the Greek mobile telecommunications' market involves a population of around 11,5 million and comprises of three providers – incumbent provider CosmOTE and alternative providers Vodafone and Wind Hellas – that offer homogenous mobile services to their subscribers (2-2.5G, 3G, 4G, 5G and VoLTE services).

This example illustrates how the proposed framework may be used to predict the providers' market share over the 15-year period and perform the associated risk and sensitivity analysis of the results.

iii. Framework Application

The proposed framework is implemented through a 4-step process:

Step 1: Market Performance Modeling

Following the market modeling approach proposed in Kanellos et al. (2021), to simulate market performance, data from the Greek mobile market were used. This data involves the

number of active subscriptions per mobile telecommunications' service provider from 1998, when the first mobile telecommunications networks were deployed in Greece, to 2013, to match the 15-year period. This data for operators and the total market are presented in Figure 1.

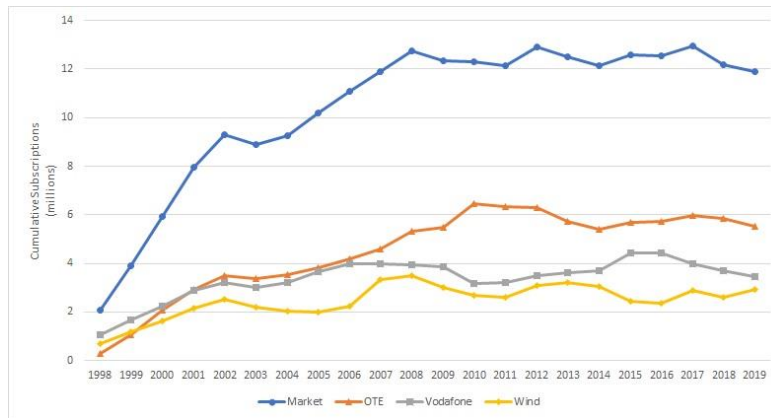


Figure 1. Diffusion of Mobile Services in Greece

It can be seen that the incumbent operator CosmOTE captures at about 50% of the entire market. The other 50% is split between the other operators, namely Vodafone and Wind.

The logistic s-curve (Eq. 6) was selected to model the market growth rate over the time period under consideration. Moreover, a volatility coefficient of 7% was used to simulate the underlying market uncertainty.

$$Y(t) = \frac{s}{1+b \cdot e^{(-ct)}} \quad (6)$$

The parameters used to model market performance are presented in Table 1:

Table 1. Market Performance Parameters

Market Modeling		
S-curve Logistic	c	0.621
	b	8.051
	S	12,036,363
Volatility	σ	0.07

Step 2: Market Performance and Customer Attraction Impact Modeling

Given the above market performance, the impact of customer attraction strategies on the providers' market share was estimated.

For every time step, the market growth was calculated. This change in the market's subscriber number was then divided to the three active providers.

The normal distribution was used to simulate the number of subscribers, as a percentage of market change, allocated to providers 1 and 2, whereas provider 3 received the remaining subscribers. Hence, subscriber allocation towards provider 3 also follows a normal distribution, whose parameters (mean and std) are externally determined. It is noted that provider 3's attraction parameters could also be selected as user defined. The aforementioned

approach was preferred because it fully supplements providers 1 and 2 modelling in terms of full subscriber allocation at any time step.

Furthermore, the normal distribution parameters differed when the market growth was negative (indicating a contraction in the market) to maintain the providers' attraction level consistent in both cases.

The parameters used to model the new market entrants' attraction towards providers are presented in Tables 2 and 3:

Table 2. Provider Attraction Modeling for Positive Market Growth

Provider Attraction Positive		
Normal	Mean	Std
Provider 1	0.5	0.05
Provider 2	0.3	0.05
Provider 3		

Table 3. Provider Attraction Modeling for Negative Market Growth

Provider Attraction Negative		
Normal	Mean	Std
Provider 1	0.2	0.05
Provider 2	0.4	0.05
Provider 3		

The change in the providers' market share at every time step was considered equal to the product of the calculated market change times the estimated subscriber allocation percentage provided by the normal distribution.

As it can be seen in Tables 2 and 3, Provider 1 was selected to be more attractive compared to the other two providers. Yet, the use of the normal distribution allows the attraction strategies of the providers 2 and 3 to overwhelm provider 1 attraction.

Step 3: Churn Modeling

To model the effects of the providers' churn management strategies to their market shares, at each time step, the number of subscribers leaving a provider for another was simulated. Again, the normal distribution was used to simulate this number, as a percentage of the provider's subscriber base. Churn Modeling parameters are presented in Table 4.

Table 4. Provider Churn Modeling

Provider Churn		
Normal	Mean	Std
Provider 1	0.15	0.05
Provider 2	0.3	0.05
Provider 3	0.4	0.05

As is suggested in Table 4, provider 1 copes best with churn management, compared to providers 2 and 3. Again, this is not true for all cases, due to the use of the normal distribution to simulate subscriber churn.

The aforementioned subscriber number was then randomly divided among the other two providers. A uniform distribution, ranging from 0 to 1, was selected to model the number of subscribers that each provider would receive.

Consequently, at the end of each time step, a provider's subscriber base was calculated as follows:

$$\begin{aligned} \text{Subscriber_base}_t &= \text{Subscriber_base}_{t-1} + \text{New_entrants}_t^{\text{Provider } i} \\ &+ \text{Incoming_churn}_t^{\text{Provider } i} - \text{Leaving_churn}_t^{\text{Provider } i} \end{aligned}$$

It is noted that the churn flows across providers were calculated based on the providers' subscriber base at the beginning of the time step under study.

A model snapshot for all framework application steps is provided in the Appendix.

Step 4: Risk-Adjusted Forecasting & Sensitivity Analysis

To complete the analysis, Monte Carlo Simulation was deployed to forecast diffusion for a period of 15 years. 10,000 samples were generated, to provide the required results. The market share of each provider at the end of this period was selected as the forecast parameter. Moreover, the provider that captured the largest market share at the end of the 15-year period was included as a forecast parameter.

For simplicity, no decision variables or restrictions, that generate a provider's market entry or exit, were modelled, as they do not affect the functionality of the framework.

iv. Application Results

The framework's application results consist of the probabilistic distribution of the providers' market share at the end of the 15-year period. Additionally, the probabilistic distribution of the market performance and a count of the times that each provider captured the largest market share at the end of this period were also calculated, as supporting data.

For the proposed simulation parameters, framework results are presented in Figure 2, whereas the market performance prediction and the winner count data are provided in Figure 3. Table 5 summarizes the statistics of the calculated probabilistic distributions.

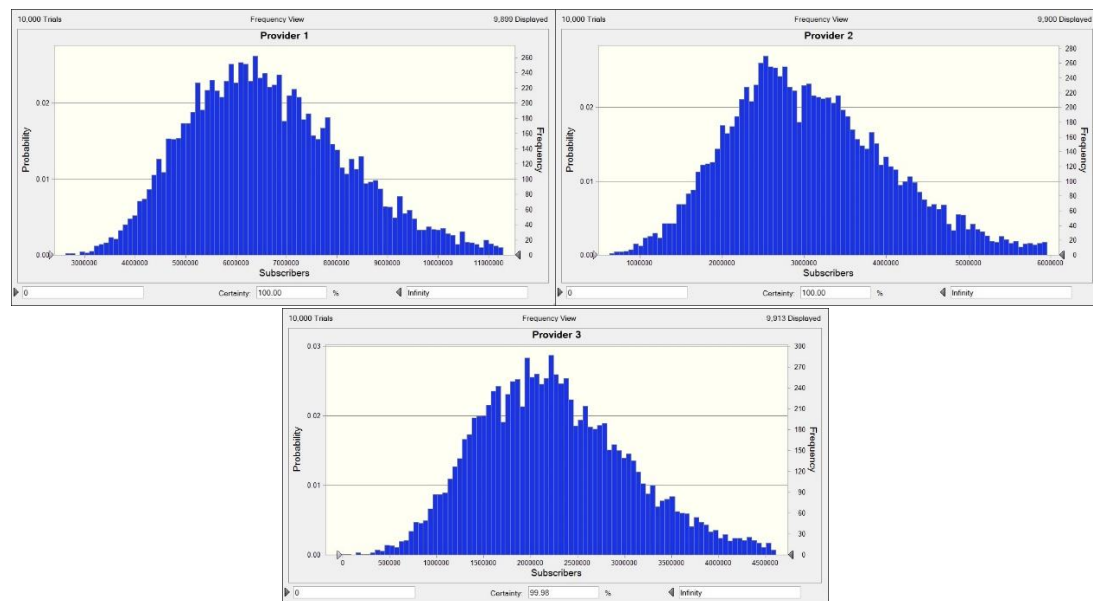


Figure 2. Probabilistic Distribution of Providers' Market Share

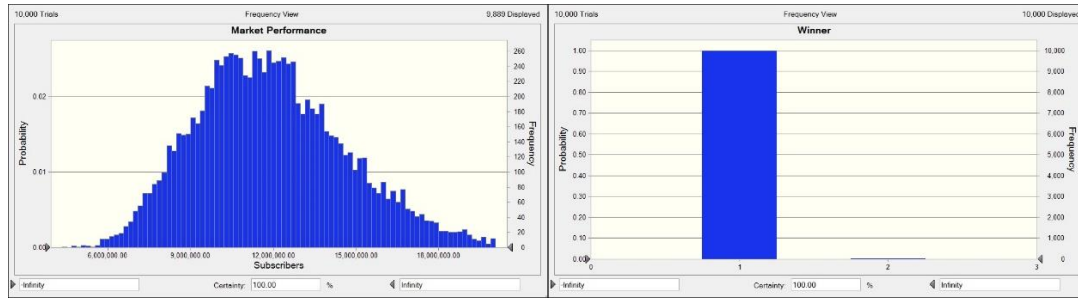


Figure 3. Supporting Data

Table 5. Monte Carlo Results Summary

Parameter	Provider 1	Provider 2	Provider 3	Total Market
Base Case*	5,689,906	2,875,073	3,531,123	12,096,101
Mean*	6,696,359	3,088,045	2,267,848	12,052,251
Median*	6,509,453	2,980,923	2,164,494	11,739,603

* Number of subscribers

The probabilistic distribution of the results enables the introduction of risk assessment techniques in the forecasting. Value-at-Risk (VAR) technique may be used to determine the probability that a provider:

- reaches a target market share or
- remains within a specific set of market share values

E.g. the application of VAR at provider 1's market share expectations indicates that there is a 25.69% probability that the market share lies within 5,5 and 6,5 million subscribers (Figure 4).

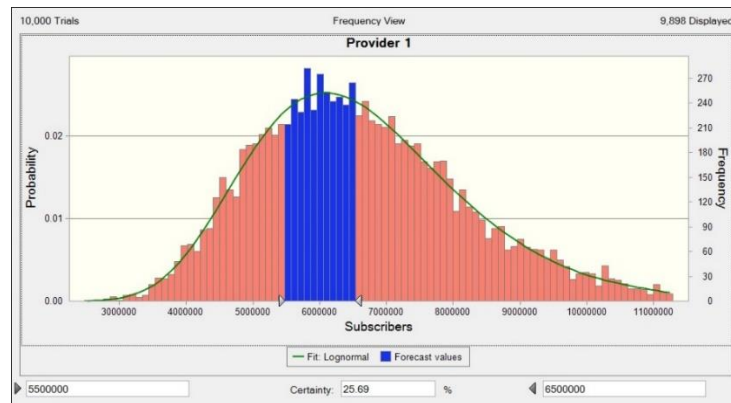


Figure 4. Provider 1's Market Share Value-at-Risk

Furthermore, competitive strategy formulation may also be aided by sensitivity analysis of Monte Carlo generated data.

A follow-up sensitivity analysis, where the mean parameter of all utilized normal distributions was allowed to vary following a uniform distribution, was carried out. Variation range was selected equal for each parameter, at ± 0.05 , except for market volatility σ , whose variation was assumed equal to ± 0.01 . This approach was selected to enable quick recognition of driver parameters in long-run market share forecast.

Sensitivity parameters are provided in Table 6.

Table 6. Sensitivity Analysis Modeling Parameters

Market Modeling			
Volatility σ	Uniform Distribution Range		
	0.06	0.08	
Provider Attraction – Positive			
Normal Dist. Parameters	Uniform Distribution Range		
	Mean		Std
Provider 1	0.45	0.55	0.05
Provider 2	0.25	0.35	0.05
Provider Attraction – Negative			
Normal Dist. Parameters	Uniform Distribution Range		
	Mean		Std
Provider 1	0.15	0.25	0.05
Provider 2	0.35	0.45	0.05
Provider Churn			
Normal Dist. Parameters	Uniform Distribution Range		
	Mean		Std
Provider 1	0.1	0.2	0.05
Provider 2	0.25	0.35	0.05
Provider 3	0.35	0.45	0.05

Sensitivity analysis results are presented in Table 7.

Table 7. Sensitivity Data

Assumptions	Contribution to Variance	Rank Correlation
Provider 1		
Provider 1 Churn	91.4%	-0.32
Provider 2 Churn	5.7%	0.08
Provider 3 Churn	1.7%	0.04
Provider 1 Attraction - Negative	0.8%	-0.03
Provider 1 Attraction - Positive	0.3%	0.02
Provider 2 Attraction - Positive	0.1%	0.01
Market Volatility σ	0%	0.01
Provider 2 Attraction - Negative	0%	0
Provider 2		
Provider 1 Churn	69%	0.32
Provider 2 Churn	29.5%	-0.21
Provider 3 Churn	0.7%	0.03
Provider 2 Attraction - Positive	0.6%	0.03
Provider 2 Attraction - Negative	0.2%	-0.02
Market Volatility σ	0%	0.01
Provider 1 Attraction - Positive	0%	0
Provider 1 Attraction - Negative	0%	0
Provider 3		
Provider 1 Churn	77.5%	0.30
Provider 3 Churn	17.9%	-0.14
Provider 2 Churn	3.4%	0.06
Provider 1 Attraction - Positive	0.5%	-0.02
Provider 2 Attraction - Negative	0.4%	0.02
Provider 2 Attraction - Positive	0.2%	-0.02
Provider 1 Attraction - Negative	0%	0.01
Market Volatility σ	0%	0

v. Result *Analysis* – Framework Validation & Discussion

Risk assessment results (Figure 2 and Table 2) suggest that Provider 1 has the higher probability to capture the higher market share among competitors. Its market share probability distribution's mean and median values are approximately half the mean and median values of the market performance probability distribution. Additionally, providers 2 and 3 have similar market share probability distributions, whose mean and median values are smaller than the ones of provider 1.

Therefore, based on these results, it is expected that provider 1 will dominate the market, by capturing more than 50% of the overall market with a probability of around 50%. The remaining 50% of the market will be divided among providers 2 and 3.

This is also suggested in the winner count support data of Figure 3, which are generated by the Monte Carlo simulation. The latter indicates that only in few cases (less than 20), provider 2 manages to acquire a higher market share than provider 1. In all other cases, provider 1 dominates competition.

It should be noted that the given risk assessment results closely interpret the actual Greek mobile telecommunications' market competition, which was used as a basis for the study. While not being an expected goal, since only the market diffusion data was utilized to model market performance and all other modeling parameters were selected arbitrarily to serve the framework verification and validation goals, the generated expectations satisfy the actual market data provided in Figure 1.

It is pointed out that this coincidence does not constitute a validation of the proposed model, rather than an indication of the proposed framework's simulation dynamics.

Furthermore, the sensitivity data provided in Table 7 indicate that the main factor driving a provider's market share expectations was the result of the churn management strategies applied by providers, as experienced by each one. Based on this data, churn has a cumulative contribution (positive and negative alike) of more than 98% to the calculated market share variance for all providers. On the contrary, attraction strategies have a contribution of about 1%, whereas market performance uncertainty has almost no effect.

Churn effects differ across providers, based on their expected market share. More specifically, market share variance for provider 1 is almost solely affected by customers leaving the provider due to churn (at 91.4%), followed by incoming customers due to churn from providers 2 and 3 (5.7% and 1.7% respectively). On the contrary, for providers 2 and 3, market share variance is benefited by provider 1 churn (at 69% and 77,5% respectively), followed by the negative impact of own churn (at 29.5% and 17.9% respectively).

Moreover, attraction strategies exhibit a contribution of about 1% to market share variance of all providers. Except for provider 3, whose attraction impact is exogenously determined by competition, this small contribution is primarily attributed to the effects of a provider's own strategies and secondarily to the effects of competitor strategies.

Last, market performance uncertainty, which is included in the estimations through the market volatility, has almost no effect on all providers' market share expectations. This is an important finding, indicating that under the proposed modelling, framework estimations are mostly affected by unsystematic risks, stemming from competition strategies, rather than market risk. Hence, market performance uncertainty does not affect the providers' performance expectation.

In conclusion, both risk assessment and sensitivity analysis results are consistent with the modeling intuition. Provider 1 was modeled as the provider with the most effective new customer attraction and churn management strategies. Thus, it was expected to have the higher probability to dominate the market. In addition, providers 2 and 3 strategies were modeled to have a similar impact. Therefore, providers 2 and 3 were expected to have a similar behavior. Moreover, sensitivity analysis results conform to the findings of the churn

management studies in the telecommunications' sector included in the validation plan, indicating that provider performance relies mostly on the successful implementation of customer service processes.

The above validate the correct operation of the proposed framework.

5. Conclusion

Telecommunication providers' market share risks stem from uncertainties due to overall market performance and competition strategies adopted by providers. These strategies involve new customer attraction and churn management.

To incorporate these uncertainties in a provider's long-run market share forecasting, in this paper, a finite-horizon, discrete time framework that allows risk-adjusted forecasting of a provider's market share was presented. The proposed framework utilizes a Markov decision process (MDP) to model the effects of churn management strategies undertaken by competitor providers. Furthermore, these providers are allowed to compete over the limited subscribers resulting from an uncertain market performance, simulated with the use of a calibrated Ito stochastic process. Finally, the impact of risks and uncertainties originating from competition strategies and overall market performance on a provider's market share expectations is explained through Monte Carlo simulation.

The use of the proposed framework was verified and validated. Data from the Greek mobile market provided a basis for overall market performance. The flexibility of the framework's application is consistent with the time series data regarding churn and attraction strategies provided by market analysis. Furthermore, framework application results validated the requirements that efficient attraction and churn management strategies lead to higher market share expectations. These expectations were found not to be affected by the market's systematic risks.

The proposed framework may be used by telecommunications providers to formulate their strategic planning. This constitutes the aim of this work. Moreover, it can be used as an aid for the determination of the impact of competitive interactions between telecommunication providers in already established markets. Furthermore, an extension is provided that enables simultaneous market structure forecasting, through the use of special decision variables and restrictions.

Acknowledgments

The work described in this article has been funded by the Special Account for Research Grants via the Postgraduate program, Management and Economics of Telecommunication Networks, Dept. of Informatics and Telecommunications, National and Kapodistrian University of Athens (N.K.U.A).

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Appendix

Market Model															
Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Market_Logistic_Model	2259645	3619766	5350527	7200826	8844530	10081208	10900282	11397950	11684646	11844758	11932629	11980393	12006219	12020145	12027642
Market_Growth_Rate		0,601918	0,478142	0,345816	0,228266	0,139824	0,081248	0,045656	0,025153	0,013703	0,007419	0,004003	0,002156	0,00116	0,000624
Drift		1360121	1544130	1661550	1399797	1002425	638345,5	388318,1	249013,7	130296,3	63222,42	34189,35	18446,75	10255,4	5266,844
Uncertainty		-390327	31149,04	-333958	-362918	-314818	10070,74	1006327	-640108	-1116895	-43937,5	-18625,1	266501,8	-407747	610046,3
Change		969794	1575279	1327592	1036879	687607	648416	1394645	-391094	-986599	19284,95	15564,22	284948,5	-397491	615313,1
Market_Subscribers	2259645	3229439	4804718	6132310	7169189	7856796	8505212	9899857	9508763	8522164	8541449	8557013	8841961	8444470	9059783

Customer Attraction															
Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Market_Change	2259645	969794	1575279	1327592	1036879	687607	648416	1394645	-391094	-986599	19285	15564	284949	-397491	615313
Provider 1_Share	55,39%	48,33%	52,80%	48,44%	40,95%	53,49%	45,53%	44,83%	20,63%	19,52%	49,35%	45,49%	47,95%	19,47%	44,37%
Provider 2_Share	25,88%	24,70%	34,65%	39,81%	26,79%	25,58%	30,06%	24,88%	35,90%	33,79%	22,26%	34,83%	25,48%	43,49%	28,86%
Provider 3_Share	18,73%	26,98%	12,55%	11,75%	32,26%	20,93%	24,42%	30,29%	43,47%	46,69%	28,39%	19,67%	26,57%	37,04%	26,78%
Provider 1_Change	1251683	468657	831804	643108	424592	367801	295196	625181	-80673	-192559	9516	7081	136632	-77383	272990
Provider 2_Change	584683	239527	545833	528501	277817	175901	194883	347008	-140404	-333356	4294	5421	72605	-172863	177552
Provider 3_Change	423278	261610	197642	155983	334470	143905	158338	422456	-170017	-460684	5475	3062	75712	-147245	164771

Churn Management															
Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Provider 1_Out_Rate		19,03%	13,13%	17,62%	16,53%	17,43%	21,43%	14,12%	22,33%	16,26%	16,59%	14,54%	15,06%	7,31%	15,85%
1_to_2_rate		19,17%	12,30%	69,04%	17,78%	48,86%	93,41%	82,03%	94,09%	92,84%	20,58%	47,52%	24,63%	15,09%	73,17%
1_to_3_rate		80,83%	87,70%	30,96%	82,22%	51,14%	6,59%	17,97%	5,91%	7,16%	79,42%	52,48%	75,37%	84,91%	26,83%
Provider 2_Out_Rate		29,12%	26,71%	36,68%	37,18%	33,82%	31,30%	25,90%	33,55%	33,74%	19,30%	31,68%	20,41%	20,55%	33,54%
2_to_1_rate		42,91%	73,49%	26,87%	10,92%	75,88%	10,69%	81,38%	36,10%	79,22%	3,90%	83,54%	75,52%	30,95%	16,12%
2_to_3_rate		57,09%	26,51%	73,13%	89,08%	24,12%	89,31%	18,62%	63,90%	20,78%	96,10%	16,46%	24,48%	69,05%	83,88%
Provider 3_Out_Rate		49,43%	32,79%	40,51%	38,43%	41,48%	42,86%	38,78%	36,24%	50,19%	39,15%	48,55%	43,73%	29,84%	38,55%
3_to_1_rate		18,95%	32,27%	79,51%	48,47%	40,50%	3,36%	63,72%	51,41%	38,00%	58,62%	27,87%	56,63%	70,05%	72,24%
3_to_2_rate		81,05%	67,73%	20,49%	51,53%	59,50%	96,64%	36,28%	48,59%	62,00%	41,38%	72,13%	43,37%	29,95%	27,76%
Provider 1_Out		238197	209454	434916	515791	580563	839249	489934	1057081	705235	777798	596846	674546	342843	752263
1_to_2		45672	25763	300249	91719	283685	783914	401898	994628	654733	160092	283644	166120	51735	550428
1_to_3		192526	183692	134667	424072	296878	55335	88036	62452	50502	617707	313202	508426	291108	201836
Provider 2_Out		170240	232148	505680	662232	585796	665242	826248	1131643	1151039	604036	888146	566491	554042	721179
2_to_1		73043	170613	135887	72327	444508	71130	672422	408544	911854	23532	741992	427796	171490	116263
2_to_3		97197	61536	369794	589905	141288	594112	153826	723099	239186	580504	146154	138695	382552	604916
Provider 3_Out		209239	250945	387760	472717	873380	777666	715389	649931	882913	276037	792718	569618	434400	596689
3_to_1		39646	80992	308323	229123	353725	26165	455810	334127	335470	161808	220923	322563	304301	431040
3_to_2		169593	169954	79436	243594	519656	751501	259578	315803	547443	114229	571795	247056	130098	165648
Provider 1_Churn_Change		-125508	42150	9294	-214342	217670	-741954	638298	-314409	542088	-592458	366069	75813	132949	-204960
Provider 2_Churn_Change		45024	-36432	-125995	-326919	217545	870173	-164772	178789	51137	-329715	-32707	-153316	-372209	-5103
Provider 3_Churn_Change		80484	-5718	116701	541261	-435215	-128220	-473526	135620	-593225	922173	-333362	77503	239260	210063
Provider 1_Total_Change		343149	873954	652402	210250	585470	-446758	1263479	-395083	349529	-582942	373150	212445	55566	68030
Provider 2_Total_Change		284551	509401	402506	-49102	393446	1065056	182236	38385	-282219	-325422	-27286	-80711	-545072	172450

Churn Management															
Year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Provider 3_Total_Change		342094	191924	272684	875731	-291309	30118	-51070	-34396	-1053910	927648	-330300	153214	92015	374834
Provider 1_Total	1251683	1594832	2468786	3121189	3331439	3916909	3470152	4733631	4338548	4688077	4105136	4478285	4690730	4746296	4814326
Provider 2_Total	584683	869235	1378636	1781141	1732039	2125485	3190541	3372777	3411161	3128943	2803521	2776235	2695524	2150452	2322902
Provider 3_Total	423278	765372	957296	1229980	2105711	1814402	1844520	1793449	1759053	705144	1632792	1302492	1455707	1547722	1922556