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5G Compartmental Diffusion Modeling in Saturated Markets

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5G Compartmental Diffusion Modeling in Saturated Markets

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Abstract

As the deployment and adoption of 5G technology continues to unfold, there is an increasing need to comprehend the key drivers that will shape its diffusion in the market. This research paper introduces a compartmental model designed to analyze the factors influencing the adoption of 5G technology, with a specific focus on user demand. The findings from the model's example analysis underscore the critical role played by machine-to-machine (M2M) communication use cases and subscriber costs in accelerating the widespread adoption of 5G technology. By offering valuable insights into the projected trajectory of 5G diffusion, this model can serve as a valuable resource for policymakers and industry stakeholders, aiding them in making informed decisions regarding policies, regulations, and strategic investments related to 5G technology.

Keywords: 5G, Diffusion Modeling, Compartmental Analysis, Uncertainty Quantification

1. Introduction

Understanding the spread of telecommunication services plays a crucial role in evaluating the economic feasibility of such technologies. This information is invaluable to telecommunications service providers as it aids them in making informed choices regarding technology adoption and expanding their capacity. Additionally, policymakers and regulators rely on this analysis to shape market dynamics and foster healthy competition.

While previous generations of mobile networks primarily focused on fulfilling human communication needs, 5G extends that scope by encompassing machine-to-machine (M2M) communications as well. By providing a robust infrastructure, it offers vast opportunities for Internet of Things (IoT) applications, such as connected sensors for creating smart cities, robots for enhancing manufacturing processes, and connected vehicles for revolutionizing human mobility. This integration of human and M2M communications in 5G networks opens up a wide range of possibilities for various industries and sectors.

On the human communication side, 5G offers faster data speeds, lower latency, and increased capacity, allowing for high-quality video streaming, real-time collaboration, and immersive experiences. It enhances the overall user experience and enables new applications such as augmented reality (AR), virtual reality (VR), and ultra-high-definition multimedia.

Simultaneously, 5G empowers machine-to-machine communications, facilitating the exchange of data between devices and enabling automation and intelligent decision-making. This aspect of 5G is particularly valuable in industrial settings, where interconnected devices, sensors, and machines can communicate and coordinate seamlessly. It enables advanced automation, remote monitoring, predictive maintenance, and efficient resource allocation across various sectors, including manufacturing, logistics, transportation, healthcare, and smart cities.

Therefore, 5G integration of both human and machine communications is a key factor driving its diffusion. It provides a comprehensive communication platform that caters to the needs of humans while enabling seamless connectivity and communication between devices, thereby fostering digital transformation across industries.

However, in the human market, 5G faces competition from various existing and emerging technologies. Previous generations of mobile networks, such as 4G, 3G, and 2G, continue to offer viable communication options for users, along with alternatives like Wi-Fi networks and fixed-line broadband connections. Users' decisions to adopt 5G are influenced by factors such as network coverage, data speeds, reliability, and pricing, which play critical roles in shaping the competition between 5G and other options in the human market.

In addition, in the M2M vertical markets, 5G encounters competition from specialized technologies designed for IoT applications. Low-Power Wide-Area Networks (LPWANs) like Sigfox, LoRaWAN, and NB-IoT, provide connectivity solutions for various M2M use cases, such as smart metering, asset tracking, and industrial automation. These technologies offer specific advantages such as long-range coverage, low power consumption, and cost efficiency, making them attractive options for IoT deployments. The choice between 5G and competing M2M technologies depends on factors like application requirements, network coverage, device costs, and scalability.

The competition among various technologies in both the human and M2M markets plays a significant role in shaping the diffusion of 5G. The availability and attractiveness of alternative options create challenges and opportunities for the adoption of 5G. The success of 5G relies not only on its technological advancements but also on its ability to effectively compete in terms of network coverage, service quality, pricing, and meeting specific market needs.

To provide future estimates for the penetration of related mobile services, previous studies in the field commonly employ diffusion of innovations theory and time-series forecasting. For instance, Smail and Weijia (2017) and Jha and Saha (2018) have utilized S-shaped diffusion models to predict the future adoption of innovative 5G services at the national level. In a similar vein, Lim and Kim (2017) have proposed the adoption of the Norton-Bass multi-generation diffusion model to forecast the introduction of 5G mobile telecommunications service specifically in South Korea. Additionally, Kalem et al. (2021) have employed the Box-Jenkins method to determine the optimal timing for 5G investments in Turkey.

While these studies contribute valuable insights into 5G diffusion, they fail to consider the broader implications of 5G adoption in multiple vertical markets on overall 5G demand. To address this gap in the existing literature, Kanellos et al. (2023) proposed a system dynamics model that incorporates the broader implications of 5G adoption in multiple vertical markets on overall 5G demand. By utilizing this approach, Kanellos et al. (2023) capture the dynamic relationships between various factors, such as market dynamics, technology adoption

patterns, and the specific characteristics of different vertical markets. The model allows for a nuanced analysis of how the adoption and utilization of 5G technology in vertical markets influence the overall demand for 5G services.

Building upon this foundation, the present study seeks to extend the work of Kanellos et al. (2023) by incorporating technology competition through the use of compartmental analysis. This approach offers a complementary perspective, allowing for a detailed examination of the interplay between competing technologies and their influence on 5G diffusion dynamics. By leveraging compartmental analysis, this study aims to enhance our understanding of the complex factors shaping the diffusion of 5G technology across various vertical markets.

The knowledge gained from this research can support informed decision-making and enable stakeholders to make strategic choices that align with the dynamic landscape of 5G deployment. These findings provide a basis for policymakers and industry leaders to navigate the complexities of the 5G ecosystem and optimize their investments and resource allocation strategies accordingly.

The rest of the paper is organized as follows: In Section 2, an overview of the proposed compartmental modeling approach for 5G diffusion is presented. Section 3 offers an illustrative example that demonstrates the application of the proposed model. Section 4 of the paper presents the results of the example application and provides a comprehensive analysis of these results. Finally, Section 5 presents the study's conclusions, summarizing the key findings and their implications.

2. 5G Diffusion Compartmental Model Overview

As the widespread adoption and diffusion of 5G technology are anticipated to be driven by both conventional human communications markets and emerging machine-to-machine (M2M) vertical markets, it is reasonable to hypothesize that the introduction of 5G in diverse vertical markets would positively influence the overall dissemination of the technology. Each market's adoption of 5G is expected to exhibit its unique pattern, indicated by the number of connected devices. By combining the diffusion patterns of 5G across various vertical markets, a comprehensive representation of the overall 5G demand can be obtained.

To assess the collective impact of 5G adoption in each vertical market on the overall demand for 5G services, this study proposes a compartmental modeling approach. The proposed methodology builds upon equation-based models, specifically compartmental models, which have been widely employed in fields such as epidemiology, engineering, and physics to describe the temporal behavior of complex systems. In this context, compartmental models can be viewed as an extension to traditional diffusion models, particularly the Bass model (Abedi, 2019).

This approach visualises 5G subscribers (human or machine, potential or active) as different compartments, with flows between these compartments and feedback loops controlling the flows. These dynamics are represented by differential or difference equations, and they simulate subscriber heterogeneity in technology selection. Model results are obtained using numerical methods and simulation.

Given the distinct characteristics of the human communications market and M2M markets, separate modeling approaches are employed to accurately capture the dynamics within each

market. This allows for a comprehensive analysis of 5G diffusion, considering the specific factors and considerations that influence adoption within each market segment.

A. Human Market Modeling

5G, as the latest generation of mobile network technology, builds upon and succeeds previous generations such as 4G (LTE), 3G, and 2G. Each mobile generation represents a significant advancement in network capabilities, data speeds, and technological features. While 5G introduces substantial improvements, it does not render previous generations obsolete. Instead, 4G and 3G networks continue to coexist with 5G, ensuring reliable connectivity in areas where 5G infrastructure is not fully deployed. This coexistence allows devices that are not 5G-compatible to still access services through the existing network generations.

To capture the transition from previous mobile telecommunications technologies to 5G, the Bass diffusion compartmental model, proposed in Sterman (2002) and Baran (2010), was employed. This model was chosen for its ability to offer valuable insights into the adoption dynamics of a new technology, including the timing and speed of adoption, as well as the roles of innovators and imitators in the process. It consists of two compartments: potential adopters (compartment A) representing active subscribers to mobile technologies and 5G potential adopters (compartment B) representing subscribers that have transitioned to 5G.

Under this approach, potential adopters, comprising of the sum of active mobile market subscribers of previous mobile network technologies, become 5G subscribers following two distinct flows: Innovators and Imitators. Innovators are the first subscribers to adopt the new technology, whereas Imitators are subscribers that follow the lead of Innovators. Therefore, both flows play crucial roles in the diffusion process of 5G, with the innovators initiating the adoption and the imitators driving further adoption through their emulation of the innovators' behavior.

It is worth noting that in saturated markets, where adoption rates stabilize, the number of potential adopters may be considered stable over the study period. Alternatively, in markets with evolving dynamics, the number of potential adopters can exhibit randomness, that may be modeled through a stochastic process. Recognizing these characteristics is crucial for studying the diffusion patterns and dynamics of 5G accurately in different market contexts.

Furthermore, to highlight the importance of user transitioning costs, such as the expenses associated with acquiring 5G-compatible mobile devices and subscribing to 5G services, a selection parameter was integrated into the proposed Bass diffusion model. This parameter accounts for the percentage of both Innovators and Imitators who successfully undergo the transition to 5G, recognizing that not all subscribers may have the financial capacity to complete the transition, despite their desire to do so. This parameter may vary between Innovators and Imitators, reflecting potential disparities in the financial circumstances of these subscriber segments. By incorporating this parameter, the model acknowledges the financial considerations and constraints that can influence the rate of adoption and diffusion of 5G technology among different user groups.

It is noted that subscribers who were unable to complete the transition to 5G due to financial constraints are not excluded from the model. Instead, they are considered as potential adopters in the future, allowing for the possibility of delayed adoption of 5G. By accounting for these potential adopters, the model recognizes that the transition to 5G may occur gradually over time as financial barriers are overcome or as more affordable options become

available. This ensures a comprehensive representation of the adoption dynamics and allows for a more accurate assessment of the long-term impact of financial constraints on the diffusion of 5G technology.

Additionally, a feedback loop is incorporated into the proposed selection parameter to capture the dynamic nature of market conditions and external influences. This enables the simulation of changing transaction costs as the technology matures, providing valuable insights into the potential impacts of policy changes or technological advancements on market outcomes.

The proposed human market compartmental model is presented in Fig. 1.

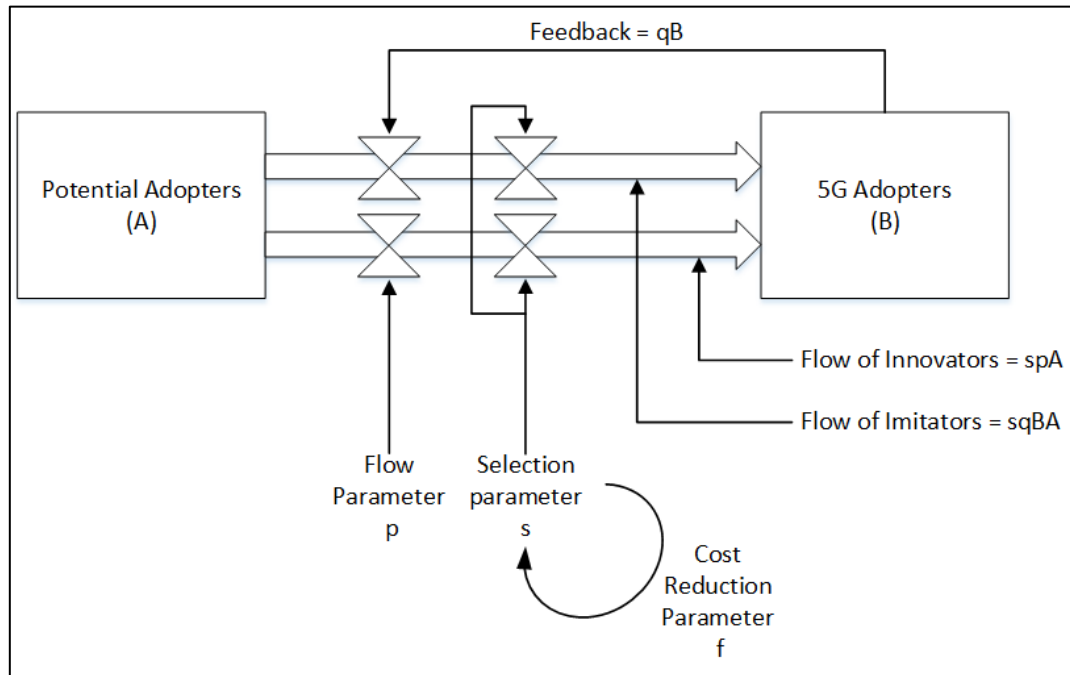


Figure 1. Human Communications Market Compartmental Model

The underlying stocks and flows are presented below:

1. flow **Probability** = $\frac{\text{Potential Adopters}}{\text{Potential Adopters} + \text{5G Adopters}}$
2. flow **Innovators** = $s \cdot p \cdot \text{Potential Adopters}$
3. flow **Imitators** = $s \cdot q \cdot \text{5G Subscribers} \cdot \text{Probability}$
4. stock **Potential Adopters** -= (Innovators + Imitators)
5. stock **5G Subscribers** += (Innovators + Imitators)

B. M2M Market Modeling

In contrast to the human communications market, where 5G faces competition from existing mobile technologies for a finite subscriber base, in a M2M market 5G encounters competition from specialized technologies designed for IoT applications, such as Zigbee, Z-Wave, NB-IoT etc.

Unlike the saturated human communications market, the maximum number of connected IoT devices in an M2M market is not fixed. It can vary over time due to the emergence of new IoT use cases and/or market growth. This information is represented by the value of the potential connected devices compartment, denoted as M . This compartment represents the total number of devices that can be connected in the market at a given time. It includes both

devices utilizing 5G technology and devices using alternative technologies, both active and potential.

When a new use case or application is introduced, the newly connected devices, regardless of their technology, are included in the overall count of connected devices. This process, whether stochastic or not, is simulated using a feedback loop to the potential connected devices compartment M to ensure accurate representation.

To track the adoption of specific technologies, two additional compartments are established: G for devices that have adopted 5G technology and O for devices utilizing other technologies, that compete with 5G. This compartment (O) represents the collective presence of alternative technologies competing with 5G in the market.

In contrast to the human communications market, where 5G diffusion is driven by both innovation and imitation, in an M2M market, the selection process is free, allowing each user to choose the technology that best suits their needs. This individualized selection process is implemented through two distinct adoption flows that originate from the potential connected devices compartment, denoted as M, and flow into the compartments representing devices utilizing 5G technology (compartment G) and devices utilizing other competing technologies (compartment O).

Besides the addition of newly connected devices, the number of 5G and other technology-connected devices in the M2M market is also influenced by device deactivation. Device deactivation can occur due to various reasons, including technology migration, technological obsolescence, device turning unserviceable, end of service, among others.

In the proposed model, device deactivation is simulated through outgoing flows from the compartments of 5G devices (G) and devices using alternative technologies (O). Each of these flows further splits into two separate flows to account for technology migration and other factors such as technological obsolescence, device unserviceability, or end of service. The flow representing technology migration is directed towards the compartment housing devices of a different technological category, indicating the transition of devices from one technology to another. The other flow is directed towards the potential connected devices compartment (M), indicating that the devices have become inactive or are no longer connected. This signifies that these deactivated devices have the potential to become new entrants in the market. By incorporating these flows, the model captures the dynamics of device deactivation and the possibility of devices re-entering the market.

It is worth mentioning that in the proposed model, the outflows from the compartment M (representing technology adoption) and the inflows into the compartment M (representing device deactivation) are treated separately. This differentiation adds flexibility to the model, allowing the practitioner to define the functions that govern each flow according to their specific requirements and objectives.

The following points are also worth considering:

1. The proposed approach extends beyond the scope of IoT devices and also includes Internet of Everything (IoE) devices. This broader perspective recognizes the interconnectedness of various devices and systems within the digital ecosystem.

2. The analysis can be conducted not only at the market level but also at the application-use case level. This granularity allows for a more detailed examination of specific scenarios and their impact on technology adoption and competition dynamics.
3. The selection process and timing of 5G adoption, as well as the introduction of competing technologies, can vary across different vertical markets and use cases. Furthermore, these variables may change over the duration of the study period. This variability is crucial for capturing potential network effects and competition-related factors that may emerge during the diffusion of 5G.

The proposed M2M market compartmental model is presented in Fig. 2.

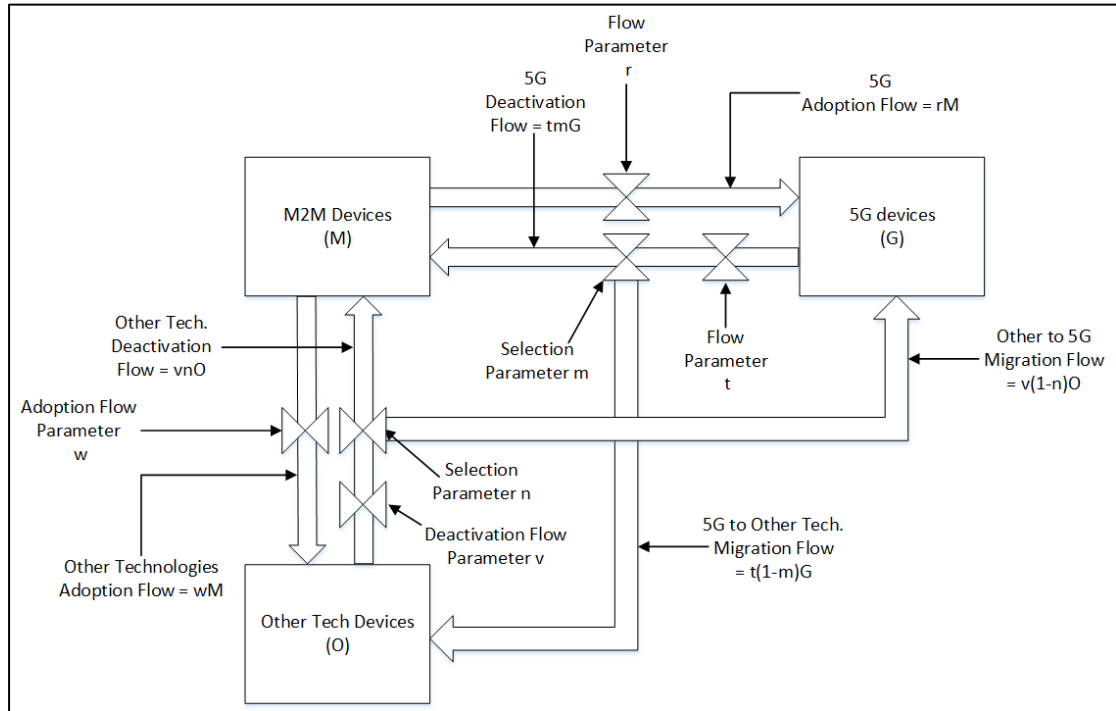


Figure 2. M2M Market Compartmental Model

The underlying stocks and flows are given below:

1. flow **5G Adopters** = $r \cdot \text{M2M Devices}$
2. flow **5G Deactivation** = $t \cdot m \cdot \text{5G Devices}$
3. flow **Other Adopters** = $w \cdot \text{M2M Devices}$
4. flow **Other Deactivation** = $v \cdot n \cdot \text{Other Devices}$
5. flow **5G to Other Migration** = $t \cdot (1-m) \cdot \text{5G Devices}$
6. flow **Other to 5G Migration** = $v \cdot (1-n) \cdot \text{5G Devices}$
7. stock **M2M Devices** += (5G Deactivation - 5G Adopters + Other Deactivation - Other Adopters)
8. stock **5G Devices** += (5G Adopters - 5G Deactivation + Other to 5G Migration)
9. stock **Other Devices** += (Other Adopters - Other Deactivation + 5G to Other Migration)

C. Overall 5G Diffusion Modeling

Following the different markets' modeling, the estimation of overall 5G demand involves aggregating the demand across vertical markets, which is quantified by the total number of connected devices. This computation considers the addition of newly connected 5G devices at each time step, allowing for the tracking of 5G diffusion over time.

Furthermore, when employing stochastic modeling of flow parameters, Monte Carlo simulation can be utilized to capture the variable interactions among market characteristics. By generating multiple potential diffusion paths for the 5G service, this approach allows for the sensitivity analysis of model inputs and the creation of a risk-adjusted forecast for overall 5G service demand. Sensitivity analysis helps identify how different inputs affect the simulation output, providing valuable insights for decision-makers. Furthermore, such a forecast acknowledges the inherent uncertainty in the projections, offering a better understanding of potential outcomes in various scenarios. This enables decision-makers to make informed decisions considering the range of possibilities and associated risks.

3. Modeling Application

While 5G technology itself has been deployed in many regions, the full implementation and adoption of 5G for IoT applications have been slower in some cases (Blind & Niebel, 2022).

In order to gain further insight into the proposed diffusion modeling approach, an example case is presented considering the absence of actual 5G market diffusion data. In this example, a telecommunications sector is examined, comprising of a main human communications market as well as four specific M2M vertical markets: automotive, industrial automation, smart agriculture, and smart cities. For simplicity, the introduction time of 5G technology is assumed to be the same across all markets studied.

The diffusion pattern of 5G technology is assessed over a 15-year period, which is considered a typical lifespan for a mobile network technology. Within this timeframe, two scenarios are implemented:

- In the first scenario, numerical inputs are used for the market parameters. This allows for estimating the market and evaluating the model's ability to provide accurate estimations. It provides a baseline understanding of the market dynamics based on specific input values.
- In the second scenario, stochastic inputs are employed to assess the impact of different parameters on model outputs and to generate a risk-adjusted market forecast. By incorporating randomness and variability into the inputs, this scenario captures the uncertainties and potential fluctuations in the market.

Through these scenarios, the model analyzes the adoption and diffusion of 5G technology in each market segment and provides insights into the potential dynamics and trends of the overall 5G technology.

A. Deterministic Scenario

In the deterministic scenario, numerical inputs are used for the market parameters and a market estimation is based on these specific input values. Thus, this scenario allows for a focused analysis of the market dynamics under predetermined conditions. This approach is useful for understanding the potential outcomes and behavior of the market when certain parameters are held constant.

Human Market Modeling

The proposed modeling methodology focuses on the adoption dynamics of 5G technology, considering it as a substitution for existing mobile technologies in the market. As proposed

earlier, the Bass diffusion model, depicted in Fig. 1, is utilized to gain insights into the adoption process.

In order to forecast the diffusion of 5G technology in the human communications market, the proposed approach utilizes five parameters: the market saturation point (S), the innovation parameter (p), the imitation parameter (q), and two additional parameters related to the technology selection process (s and f).

The market saturation point (S) represents the maximum number of potential adopters in the market, indicating the point at which the market becomes saturated with 5G technology. The innovation parameter (p) captures the effect of innovation in driving the initial adoption of 5G, reflecting the willingness of early adopters to embrace new technology. The imitation parameter (q) represents the influence of social interactions and the adoption behavior of others on the decision-making process of potential adopters.

The two additional parameters, technology selection parameters (s and f), play a role in determining the choice of technology by potential adopters. The parameter s represents the number of subscribers who successfully overcome the expenses associated with transitioning to 5G technology, whereas the parameter f represents the reduction of transition costs over time. These parameters may vary between innovators and imitators. For simplicity, in the given scenario, both parameters are considered equal for all types of subscribers. In addition, as the feedback parameter f is kept constant, the selection parameter s exhibits a steady annual increase. This gradual increment persists until the value of s reaches 1, signifying that all subscribers have the financial capacity to bear the expenses associated with migrating to 5G technology.

The values of the parameters used in the model for the human communications market are presented in Table I for reference.

Table I. Human Market Deterministic Model Parameters

Parameter	Value
Population A	10,000,000
p	0.2
q	0.3
s	0.5
f	0.05

It is important to note that these values are provided for illustrative purposes and may vary in different scenarios or real-world applications.

M2M markets modeling

To capture the saturation point of a machine-to-machine (M2M) vertical market, the maximum allowable number of connected devices is determined. This number is expected to increase over time as new IoT or IoE use cases emerge. In the proposed model, this increase is simulated using a Poisson process with a constant jump parameter λ , which generates random arrivals of new potential devices. In addition, the jump size is held constant throughout the simulation. Consequently, the number of potential connected devices in compartment M at every time step is calculated by adding the existing potential devices to the devices introduced through the jump process.

According to the proposed M2M market modeling depicted in Figure 2, six parameters are employed to describe subscriber flows within the market. These parameters include the adoption rates of 5G technology (parameter r) and other technologies (parameter w) by new devices, the rates of device deactivation (parameters t and v) for 5G and other technologies respectively, along with the proportions of deactivated devices that migrate to a different technology or return to the potential devices compartment M (parameters n and m). In the given scenario, all six parameters are kept constant.

The proposed compartmental model is replicated for each of the four M2M markets under study, namely automotive, industrial automation, smart agriculture, and smart cities.

To reflect the distinct dynamics of 5G adoption in each market, different parameter values are assigned in the model. These parameter values are determined based on the specific characteristics and expectations of the respective M2M markets. The values of the parameters employed in the example application for M2M market modeling are presented in Table II.

Table II. M2M Market Deterministic Model Parameters

M2M Market	Automotive	Industrial Automation	Smart Agriculture	Smart City
Parameter	Value	Value	Value	Value
Saturation M	5,000,000	1,500,000	750,000	7,500,000
r	0.3	0.1	0.3	0.3
w	0.05	0.4	0.05	0.3
t	0.05	0.25	0.25	0.15
v	0.05	0.25	0.25	0.15
m	0.01	0.1	0.1	0.5
n	0.9	0.5	0.75	0.5
λ	0.4	0.5	0.5	0.4
Jump Size	500,000	100,000	50,000	650,000

Several noteworthy observations can be made regarding the specific characteristics of each M2M market:

1. In the automotive and smart agriculture markets, there is a significant preference for the adoption of 5G technology. This is reflected in the higher values of parameters r and n , indicating a strong inclination towards selecting 5G over alternative technologies in these markets.
2. The industrial automation and smart agriculture markets experience relatively higher rates of device deactivation. This can be attributed to the harsh working environments and demanding operational conditions in these sectors. The parameters t and v , which determine device deactivation, are set accordingly. Additionally, the smaller value of parameter m suggests a lower likelihood of migrating deactivated devices to different technologies. On the other hand, in the automotive market, where vehicles generally have longer lifespans, the opposite scenario is considered, with lower device deactivation rates.
3. The research and development (R&D) activities leading to the introduction of innovative IoT use cases are assumed to be similar across all markets. This implies that

the potential for the emergence of novel IoT applications and use cases is consistent across the automotive, industrial automation, smart agriculture, and smart cities markets.

Again, the values of parameters provided in Table II are for illustrative purposes only. In real-world applications or different scenarios, these parameter values may vary depending on various factors such as market conditions, technological advancements, user preferences, and other contextual considerations.

B. Stochastic Scenario

In the stochastic scenario, stochastic inputs are used to assess the impact of uncertainty of different input parameters on model outputs and the generation of a risk-adjusted market forecast. This scenario provides insights into potential outcomes across different scenarios and aids the decision-making process under uncertain conditions.

Human Market Modeling

To incorporate variability and address the inherent uncertainty in the proposed model, the evolution of the market saturation point is simulated using a wiener process. The wiener process introduces random fluctuations over time, reflecting the unpredictable nature of market dynamics.

Furthermore, in order to facilitate a comprehensive analysis of the model's sensitivity to different input parameters, it is assumed that all five input parameters follow a uniform distribution. This choice allows for a wide range of potential values for each parameter, enabling a thorough exploration of their impact on the model's output.

It is important to note that in the model, the value of each parameter is subject to random variation at each time step. This stochastic element adds further complexity and realism to the model, enabling a more accurate assessment of the potential outcomes and future trends in the market. Moreover, the upper barrier of 1 for the selection parameter s is maintained, similarly to the deterministic scenario.

The values of the parameters used in this scenario to model the human communications market, along with their respective distributions, are presented in Table III. Once again, these values are provided for demonstration purposes and may vary in different scenarios or real-world applications.

Table III. Human Market Stochastic Model Parameters

Parameter	Distribution	Value	
		Min	Max
Population A	-	10,000,000 devices	
A volatility σ	Wiener	0,1	
p	Uniform	0.1	0.4
q		0.2	0.5
s		0,3	0,5
f		0,01	0,1

M2M Markets Modeling

To begin with, in the stochastic model, market saturation variability is achieved through two methods. Firstly, the market saturation point is determined using a Wiener process, introducing random fluctuations over time. Secondly, the jump parameter λ , which represents the probability of potential devices added to the M compartment at a given time step, and the jump size, indicating the magnitude of this addition, follow uniform distributions. These stochastic components add uncertainty to the model and allow for a more realistic representation of market dynamics.

In addition to the market saturation variability, the characteristic parameters of the market are also assumed to follow a uniform distribution. This assumption allows for a range of possible values for these parameters, taking into account the inherent uncertainty and variability in the market.

Similar to the deterministic scenario, in the stochastic scenario, the proposed compartmental model is replicated for each of the four M2M markets being studied: automotive, industrial automation, smart agriculture, and smart cities. This replication allows for the individual modeling and analysis of each market, taking into account their unique characteristics and dynamics.

It is important to note that the values of the modeling parameters used in the stochastic scenario were derived from the market intuitions and insights obtained in the deterministic scenario. The parameter values were selected to reflect the specific characteristics and dynamics of each M2M market under study. However, in the stochastic scenario, the values of these parameters are allowed to change randomly at each time step, introducing variability and capturing the inherent uncertainty of real market conditions.

Table IV presents the values of the parameters used in the stochastic scenario for M2M market modeling, providing insight into the specific parameter settings that have been employed to simulate the adoption process for 5G technology in each market segment. These values are provided for illustrative purposes and may vary in different scenarios or real-world applications.

Table IV. M2M Market Stochastic Model Parameters

M2M Market		Automotive		Industrial Automation		Smart Agriculture		Smart City	
Parameter	Distribution/ Process	Value		Value		Value		Value	
		Min	Max	Min	Max	Min	Max	Min	Max
Population M	-	5,000,000		1,500,000		750,000		7,500,000	
M_Volatility_σ	Wiener	0.05		0.1		0.05		0.2	
r	Uniform	0	0.3	0	0.1	0	0.3	0	0.3
w		0	0.05	0	0.4	0	0.05	0	0.3
t		0	0.1	0.2	0.4	0.2	0.4	0.1	0.2
v		0	0.1	0.2	0.4	0.2	0.4	0.1	0.2
m		0	0.02	0.05	0.2	0.05	0.2	0.35	0.65
n		0.5	0.95	0.35	0.65	0.5	0.9	0.35	0.65
λ		0.3	0.5	0.35	0.65	0.35	0.65	0.3	0.5
Jump Size			150,000	750,000	10,000	200,000	10,000	100,000	250,000

4. Application Results and Discussion

Following the proposed modeling approach, the total number of newly connected devices that utilize 5G technology is determined by summing all relevant flows associated with 5G

during a specific time step. This provides insights into the diffusion pattern of 5G technology over the studied time period, as well as the total number of active and potential devices, the devices utilizing competing technologies, and the remaining population of potential adopters.

The modeling results for the deterministic scenario, as shown in Fig. 3, demonstrate the 5G diffusion over a 15-year period.

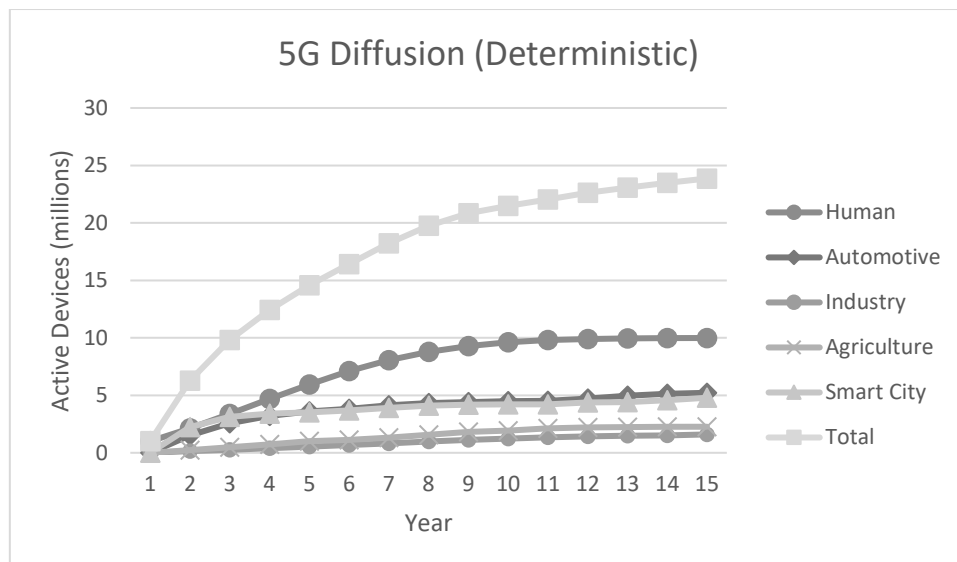


Figure 3. 5G Diffusion – Deterministic Scenario

As it can be seen in Fig.3, the human market plays a significant role in driving the adoption of 5G technology, representing nearly half of the connected devices and reaching market saturation after 10 years. Following closely are the automotive and smart city M2M markets, which exhibit a high potential device base and a strong preference for 5G technology. On the other hand, the smart agriculture and industrial automation markets, which do not exhibit a strong preference for 5G, follow behind in terms of 5G adoption.

Furthermore, in Fig. 4, the distribution of the device population is depicted, showing the allocation between 5G and other competing technologies, as well as the remaining potential connections.

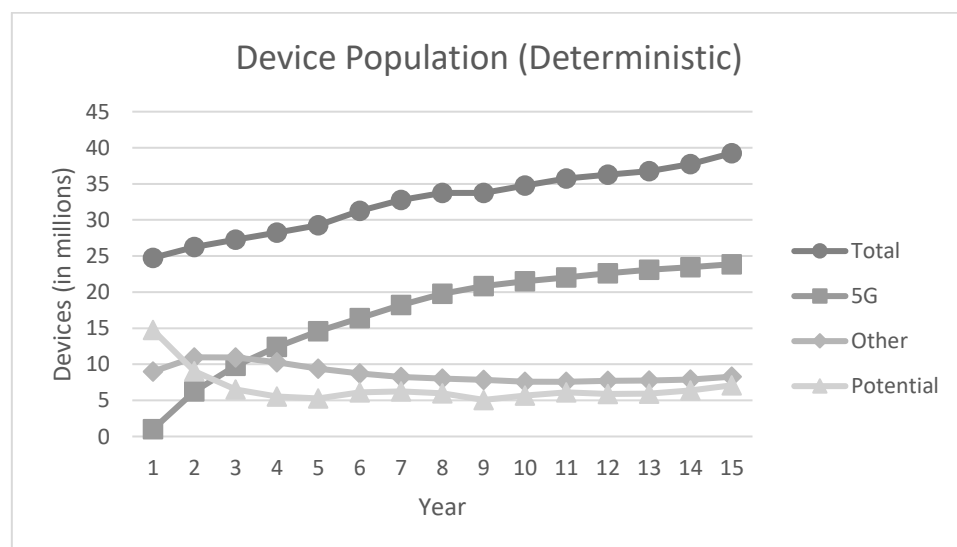


Figure 4. Device Allocation – Deterministic Scenario

Fig. 4 highlights that the number of 5G connected devices is consistently growing over time. On the other hand, the number of devices utilizing other technologies gradually diminishes, primarily as a result of the replacement of previous mobile technologies by 5G in the human communications market. However, an interesting trend emerges after the first 10 years, where the number of devices utilizing other technologies begins to rise again. This increase can be attributed to the adoption of these technologies by devices in the M2M markets, reflecting the specific dynamics and preferences within those sectors.

Moreover, considering the inherent uncertainty and variability of the stochastic model's parameters, a Monte Carlo simulation is employed. This simulation generates multiple potential diffusion paths for 5G technology, incorporating the effects of uncertain factors on adoption and usage patterns. The outputs of the simulation include a risk-adjusted forecast for the overall demand of 5G technology. This forecast provides valuable insights into the potential impact of varying uncertainties on the adoption and usage of 5G technology, as described in Section 3B above.

The results of the Monte Carlo simulation, depicting the distribution of the forecasted 5G device population at the end of the 15-year period, are presented in Fig. 5.

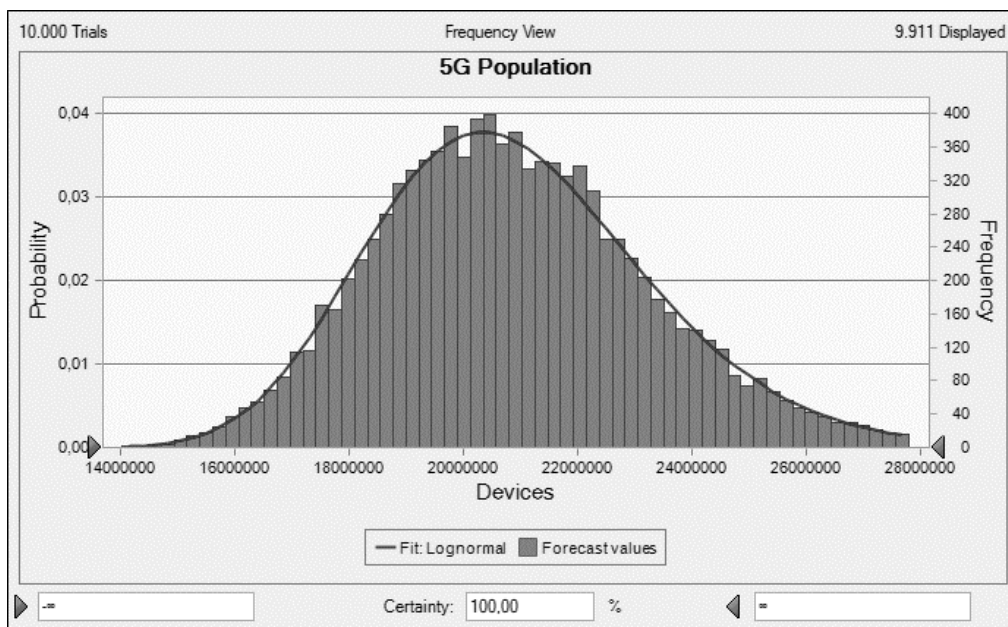


Figure 5. 5G Device Risk – Adjusted Forecast

Based on the risk-adjusted forecast outcomes using the proposed modeling approach, it is projected that the quantity of active 5G devices at the end of the 15-year period will follow a lognormal distribution. The mean value of this distribution is estimated to be $\mu = 20,901,986$, with a standard deviation of $\sigma = 2,451,187$. Additionally, in the base case scenario, the model predicts a total of 20,133,071 connected 5G devices at the end of the 15-year period. It's important to note that this is the expected outcome based on the given parameters and assumptions. However, there is variability in the forecast, and the maximum estimated number of connected devices is projected to be 34,624,265, while the minimum is estimated to be 13,780,764.

Similarly, the results of the Monte Carlo simulation show that the population of devices adopting a competing technology to 5G also follows a lognormal distribution. The mean value of this distribution is estimated to be $\mu = 6,012,155$, with a standard deviation of $\sigma = 1,408,639$.

In the base case scenario, the model predicts 6,066,764 connected devices adopting the competing technology. In addition, the maximum number of connected devices in this category could reach 14,694,763, while the minimum is estimated to be 2,203,526.

These simulation results are depicted in Figure 6, providing insights into the range of potential outcomes and the level of uncertainty associated with the adoption of competing technologies in the market.

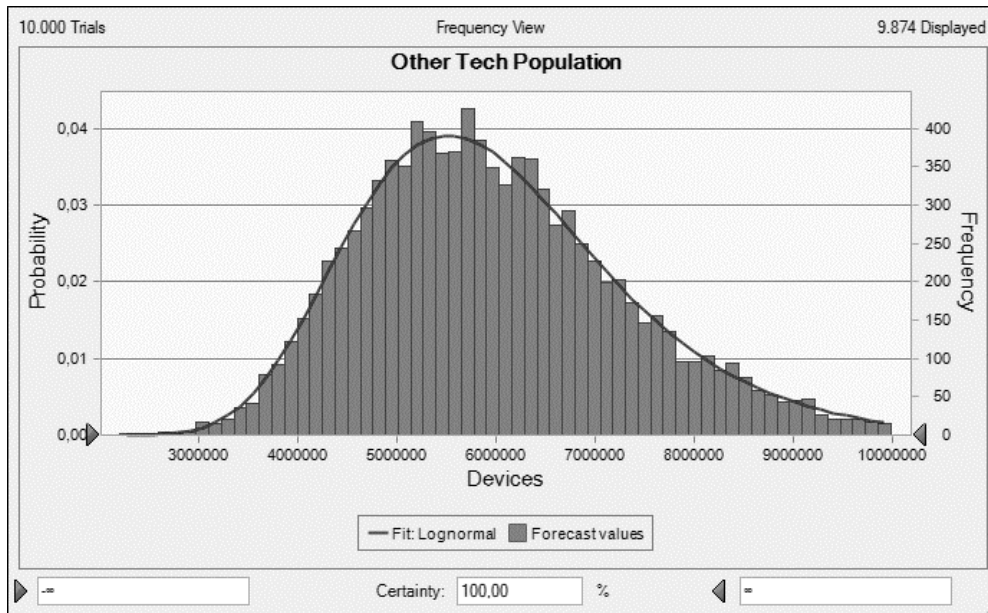


Figure 6. Devices Utilizing Other Technologies Risk - Adjusted Forecast

In order to assess the influence of individual parameters on the modeling results, a global sensitivity analysis was conducted for the 5G device population. This analysis involved sampling model parameters from a uniform distribution with a range of +/- 10% around their specified values.

Global sensitivity analysis results are presented in Table V. It is noted that only the parameters that contributed more than 1% to the variation in the total 5G device population at the end of the 15-year period are included.

Table V. Global Sensitivity Analysis Results

Contribution to variance		
Parameter	Value	Contribution
Human Communications market device starting population	+61,4%	Positive
Automotive M2M market potential device starting population	+11,6%	Positive
Smart City M2M market potential device starting population	+5,3%	Positive
Smart City M2M market 5G adoption flow r maximum value	+2,8%	Positive
Automotive M2M market 5G adoption flow r maximum value	+2,6%	Positive
Smart City M2M market Poisson parameter λ maximum value	-1,5%	Negative
Automotive M2M market device population jump size maximum value	+1,2%	Positive
Automotive M2M market Poisson parameter λ minimum value	-1,2%	Negative
Smart City M2M market other technologies deactivation flow parameter v maximum value	+1%	Positive

Based on the global sensitivity analysis results, the three parameters with the highest positive contributions, accounting for 78.3% collectively, are the starting maximum potential device population in the human communications, automotive, and smart city markets. These markets, as identified in the deterministic analysis, play a significant role in driving the overall 5G device population. Following these parameters, the maximum adoption flow parameter (r) in the automotive and smart city M2M markets also contributes positively to the variation.

On the other hand, the parameter with the highest negative contribution (-1.5%) is associated with the maximum value of the Poisson parameter that determines jumps in population within the smart city market. This parameter indicates a potential decrease in the adoption rate or growth of 5G devices within the smart city market, leading to a negative impact on the overall 5G device population forecast.

Table VI presents the contributions of each market to the variability of the 5G device population at the end of the 15-year period.

Table VI. Contribution to 5G Device Population Variability by Vertical Market

Contribution to variance		
Parameter	Value	Contribution
Human Communications	+63,1%	Positive
Automotive	+19,4%	Positive
Smart City	+14,1%	Positive
Smart Agriculture	-1,8%	Negative
Industrial Automation	+1,5%	Positive

The human market has the highest positive contribution, accounting for 63.1% of the total variability. This indicates that the human communications market plays a dominant role in driving the variation in the 5G device population.

Following the human market, the automotive M2M market has a positive contribution of 19.4%, while the smart city market contributes positively with 14.1%. These markets also have a significant impact on the overall variability of the 5G device population.

In contrast, the smart agriculture and industrial automation M2M markets have relatively smaller effects on the 5G population, with contributions of less than 2%. The smart agriculture market, in particular, exhibits a negative impact with a contribution of -1.8%, indicating a potential decrease in the 5G device population within this market.

Last, the cumulative contribution of the M2M markets is 36.9%, while the human communications market accounts for 63.1% of the total variability. These findings highlight the dominant role of the human market in driving the adoption and diffusion of 5G technology, while the M2M markets have a relatively smaller impact on the overall 5G device population.

Considering the results of the global sensitivity analysis, the stochastic model parameter value assumptions, and the findings from the deterministic model, it becomes clear that the main driver of the 5G population is the number of potential 5G connected devices, coupled with the preference towards 5G technology.

The deterministic model demonstrates that 5G technology is capable of capturing the entire human communication market within a period of 10 years, indicating a significant migration of mobile network subscribers towards 5G. This highlights the strong preference for 5G applications in the human market, driving its contribution to the overall 5G device population.

In addition, despite the smart city M2M market having a larger potential device population (7.5 million devices) compared to the automotive market (5 million devices), the strong preference for 5G applications in the automotive market positions it as the second-largest contributor to the 5G population. This suggests that a higher number of devices in the automotive market are expected to utilize 5G technology compared to the smart city market.

Furthermore, the M2M markets with smaller starting device populations, such as industrial automation and smart agriculture, have a relatively smaller impact on the overall 5G population, despite the strong preference towards 5G in the smart agriculture market. This indicates that the initial device population size plays a role in determining the influence of a specific market on the 5G population.

Overall, the findings highlight the significance of the potential 5G device base and the preference for 5G technology in driving the adoption and diffusion of 5G, with the human communications market playing a dominant role.

5. Conclusion

In this paper, a compartmental model is proposed to forecast the diffusion of 5G technology and provide insights into the potential factors influencing the adoption of future 5G technology, particularly focusing on user demand. The model's effectiveness is demonstrated through an example application that simulates the dynamics of 5G technology adoption.

The analysis highlights the importance of two key factors in driving the diffusion of 5G technology: the presence of 5G use cases and the preference for utilizing this technology. These factors have a significant impact on the overall adoption and diffusion of 5G technology.

Firstly, the existence of 5G use cases plays a crucial role in driving the adoption of this technology. The identification and development of compelling use cases that leverage the unique capabilities of 5G, such as high data rates, low latency, and massive connectivity, are essential in attracting users and driving the demand for 5G services.

Secondly, the preference towards the use of 5G technology significantly influences its diffusion. Users' willingness to adopt and migrate to 5G technology plays a vital role in its overall adoption rate. Factors such as the perceived benefits of 5G, improved user experience, and the availability of compatible devices contribute to users' preference for 5G over other existing technologies. This preference drives the demand for 5G services and leads to a higher adoption rate.

By highlighting these factors, the analysis underscores the need for the development of compelling use cases and the importance of creating a positive user experience to drive the widespread adoption of 5G technology. It also emphasizes the significance of understanding users' preferences and addressing their needs to encourage the adoption and diffusion of 5G technology.

These insights can inform stakeholders, including policymakers, network operators, and service providers, in their strategic planning and decision-making processes. By focusing on developing attractive use cases and addressing user preferences, they can effectively drive the adoption and diffusion of 5G technology, ultimately realizing its full potential and reaping the benefits it offers.

Future research could extend the proposed model to include other factors, such as regulatory frameworks, network infrastructure, and technological capabilities, to gain a more comprehensive understanding of the 5G technology adoption process and to explore the adoption dynamics of the upcoming 6G technology.

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