Integrating System Dynamics into Predictive Analytics for Dynamic Mobile Network Capacity Planning

JEAN CLAUDE MUDILU KAFUNDA[1], WITESYAVWIRWA VIANNEY KAMBALE[2], KELVIN EGBINE[2], MOHAMED ALSISI[2], KYANDOGHERE KYAMAKYA[2]

[1]Ecole Doctorale en Sciences de l'Ingenieur,
Faculté Polytechnique,
Université de Kinshasa,
CONGO

[2]Institute for Smart Systems Technologies,
Universität Klagenfurt,
Klagenfurt,
AUSTRIA

Abstract: This work assesses how System Dynamics (SD) complements Predictive analytics for dynamic mobile network capacity planning. Including SD within predictive analytics models improves responsiveness to the challenges posed by dynamic environments by including stocks and flows, feedback and time delays, and therefore model accuracy. Even with advances in machine learning, traditional predictive analytics still struggle with the dynamic feedback mechanisms as much. This research seeks to enhance mobile network forecasting and capacity planning using a hybrid approach employing real-time data. While computational complexity is a challenge, this integrated approach considerably improves network performance and planning accuracy.

Key-Words: System Dynamics, Predictive Analytics, Mobile Networks, Network Capacity Planning.

Received: June 11, 2024. Revised: November 29, 2024. Accepted: December 26, 2024. Published: December 31, 2024.

1 Introduction

The adoption of System Dynamics (SD) in predictive analytics is substantial progress in planning the capacity of mobile networks, other than the conventional approaches. The most common predictive analytics approaches, stereotyped by heavy use of historical data and statistical models, only help a little to meet the challenges of mobile networks' dynamic features, [1]. These networks have non-linear characteristics and constantly varying user needs, so achieving sustainable optimal performance and capacity becomes difficult, [2]. SD is well-suited for capturing these complexities through stocks and flows, feedback loops, and time delays. These are integral elements for modeling dynamic interactions within the network structure, [3].

Tools of System Dynamics, like [4], have proven their worth in formulating interrelationships and their changes over time in the context of complex systems, which in this case is a mobile network. These tools make it possible to develop complex models that consider the various factors that affect the network's performance, which cannot be achieved using only traditional predictive models. The prospect of combining SD with forecasting models, [5], makes it possible to create models that estimate the network's expected future demand and are updated in response to real-time changes.

This integration is crucial due to an ever-increasing complex structure of mobile networks, [6]. In this context, users demand for data is constantly increasing due to high throughput and low latency requirements applications, which raises more capacity-related planning issues. Static models are utilized in most capacity planning approaches supplemented by periodic calibration and are ineffective in such ever-changing aspects as mobile networks, [7]. In addition, recent systematic reviews on resource allocation schemes for 5G networks underscore the need for adaptive capacity planning strategies [8]. A combination of SD and predictive analytics offers a better strategy, enabling network planners to optimize the network and make better decisions, as forecasting methods have been demonstrated to enhance capacity predictions [9].

This paper investigates the possibility of employing SD as a forecasting capability for planning mobile networks' capacity. We start by presenting various theoretic approaches and the actual level of development within the field; then, we look into the elements and the factors affecting mobile communications systems. Next, we provide a comprehensive account of the said integration process and the advantages and weaknesses of this hybrid approach. To finish, we present some practical issues related to the application of integrated models in the actual world and discuss possibilities for further development.

2 Theoretical Background

The last few decades have been notable in the evolution of mobile network capacity planning due to increasing user demand and the remarkable pace of change in technology. The more conventional viewpoints on capacity planning have depended on forecasting future network demand based on historical information and statistical models, which make it possible – predictive analytics. Most predictive models generate forecasts through information sources such as network logs, users' behavior, and traffic patterns. Time series and regression analysis, and most recently, various machine learning algorithms, have been used to improve prediction accuracy.

Nevertheless, traditional predictive analytics methods have limitations despite improvements in this respect. There is often evidence of processes like dynamic feedback loops and time lags, which are pivotal in understanding the operations within mobile networks. For example, a rapid increase in the demand of users can cause the network to jam, which, in turn, impacts user behavior, making it more challenging to plan capacity appropriately. Such dynamic interactions need to be more adequately addressed by static models, which lead to better network performance and misuse of resources in terms of planning capacity.

System Dynamics (SD) offers a viable solution to these limitations by providing a robust framework for modeling complex systems characterized by dynamic interactions. SD incorporates elements such as stocks, flows, feedback loops, and time delays, which are essential for capturing the non-linear behaviors inherent in mobile networks. Tools like Vensim and Stella facilitate the creation of detailed SD models that simulate interactions between various network components over time. These models provide a holistic view of the system, allowing network planners to understand underlying dynamics better and make more informed decisions.

System Dynamics (SD) can resolve these gaps since it is a powerful approach to describing individual elements' interaction in evaluating complex model systems. SD-system elements like stock flows, feedback, and time lags are vital in capturing the nonlinearities present in mobile networks. Programs such as Vensim and Stella make it easy to create complex SD models representing interactions among network components over time. Once again, these models give a complete system view, enabling network planners to comprehend designs of the underlying dynamics and exercise more sound judgment.

There have been considerable advancements in how mobile networks are planned, designed, and optimized, integrating AI and real-time analytics into planning and designing processes. These mechanisms allow users to fetch and have insights into ever-changing real-time data more accurately and efficiently. Nevertheless, these models are still based on static behavioral descriptions and are held to frequent recalibration to account for changing patterns and long-term trend evolution. Reference argues that over the past decade, planning mobile network quantity has been more difficult due to the rapid growth in traffic demand. The growth rate may differ from one market to another; it generally averages a doubling of traffic every two years, akin to Moore's Law.

This expansion, accompanied by the volatility in network performance, calls for better capacity planning. In order to meet these challenges, integrating system dynamics (SD) into predictive analytics provides an approach that embeds feedback and lag structures into predictions. This hybrid approach improves the efficiency and the speed of response of models and, thus, assists network planners in predicting and managing the required capacity more effectively. Therefore, using SD in predictive analytics is a better alternative for planning dynamic mobile network capacity by combining real-time information with prediction models.

3 Research Questions

The combination of System Dynamics (SD) with predictive analytics in mobile network capacity and performance analysis creates several meaningful research perspectives. To guide this exploration, three such research questions have been formulated:

1. **In what ways can both System Dynamics and predictive analytics methodologies be merged to improve the accuracy of mobile network capacity planning?** This question aims to assist in the understanding of methods and techniques needed for successfully embedding system dynamics in predictive analysis. The emphasis here is on exploring the essential elements of SD, including stocks, flows, feedback mechanisms, and time dependencies relevant to increasing the effectiveness of predictive models and their components. Also, it entails identifying the appropriate data and computational tools that facilitate seamless integration and how this integration affects the performance, accuracy, and reliability of capacity planning models.

2. **In what ways does the hybrid approach composed of System Dynamics and machine learning pose benefits and challenges when**

combined in the context of dynamic mobile networks? This question intends to verify the benefits and problems that may arise related to integrating SD and machine learning in mobile network capacity planning. It is about considering how much better the prediction performance and the network, in general, can become owing to this hybrid combination. Also, the question addresses the barriers to implementation, such as example, computation burden, data requirements, and scale of the integrated models.

3. **To what extent does implementing System Dynamics in predictive analytics improve the scalability and computational effectiveness of mobile network capacity planning models?** This question examines the implications of SD integration within the scope of scalability and computational efficiency of planning models. It encompasses evaluating computational resources worth deploying integrated models and how such models perform within dynamic network structural environments. In addition, the question aims to provide insights on how integrated models may be improved by structures from recent progress in cloud computing and big data platforms.

The goal of answering these research questions is to gain a holistic perspective on the opportunities and difficulties posed by integrating SD into the recommended mobile network capacity planning practices. The outcomes of this study will help formulate more adaptive and effective strategies for capacity planning, which will improve the performance and reliability of mobile networks.

4 System Dynamics and Predictive Analytics Integration

Combining System Dynamics (SD) and predictive analytics in mobile network capacity planning offers an effective solution to the challenges associated with dynamic networks' environmental settings. As far as standard predictive analytics approaches are reasonably successful, they often need to pay more attention to elements such as feedback loops and time lags on mobile networks. Such deficiencies may result in poor network performance and poor capacity planning. The integration of SD with predictive models helps to add a more holistic understanding of network dynamics, leading to more improvements in the precision and responsiveness of capacity planning.

Integrating system dynamics into predictive models enables the incorporation of feedback loops into predictive models, which is one of the main benefits of integrating SD into predictive models, [4]. Understanding the dynamic relationships between different components of a mobile network can be done by feedback loops. For example, suppose there is a higher-than-normal demand from the users. In that case, the traffic on the network will be higher, affecting the users' actions subsequently, making the network capacity planning quite complex. With feedback mechanisms embedded into these predictive models, they can more accurately capture these phenomena and correctly estimate the future demands for the network.

Besides feedback loops, there are also stocks, flows, and time delays in SD models, [4], which shape the structure in a fundamental way for simulating the mobile networks' nonlinearities. Stocks would mean the total amount of resources/capacities built over a period, while flows would be the amount of resources added or used at a particular moment. Time delays are a more general concept used in most sciences; here, it will describe the lag between changes in one part of the network and their subsequent effects on other components. These components allow SD to address the issues in predicting network performance and offer insights beyond those provided by traditional predictive analytics.

Integrating SD with predictive analytics is likely more effective when real-time data is incorporated. Real-time data helps align the models with the present state of the network, bringing relevance to capacity planning measures. For example, by including real-time traffic in SD models, network planners could anticipate trends and persisting factors causing the bottlenecks, enabling proactive adjustments to capacity planning.

Hybrid modeling techniques, which comprise the integration of SD with ML methodologies – which include decision trees, neural networks, or other ML algorithms – allow the improvement of predictive models, [2]. This technique uses previously acquired information to understand the former behavior exhibited by the network while accommodating emerging trends. For instance, ML algorithms can analyze historical traffic patterns to predict future demands. At the same time, SD models ensure a structural ability to depict dynamic relations within a network system. Integrating these two approaches allows more accurate, flexible, and accurate predictive models to be developed. Once the evolving condition of the network is established, the model can be modified to achieve optimized performance of the models.

5 Scenario Analysis and Simulation

Using scenario analysis or simulation is essential in integrating System Dynamics (SD) into predictive analytics as far as capacity planning of the mobile network is concerned. For instance, through scenario simulation, network planners can gauge the effects of various capacity planning measures while assessing the prospects of challenges. This enables all predictive models to be evaluated and more efficient capacity planning techniques to be designed. For example, network planners can simulate the effects of different traffic growth models on the network and make informed decisions regarding capacity investments.

However, further issues must be addressed even after the seamless integration of SD and predictive analytics. Building and understanding models is inherently more challenging due to the dynamic nature of mobile networks. The coupling between network components can be intricate and complex to capture accurately. Furthermore, the integration stage is computationally heavy and resource-demanding, calling for advanced architectures and efficient algorithms. Such obstacles require a more collaborative strategy that harnesses SD and predictive analytics benefits.

Our discussion thus far indicates that incorporating SD in predictive analytics of mobile networks poses a potential improvement in the capacity planning of the mobile network. It appears more realistic that integrating SD and predictive analytics will yield predictive models that are accurate and robust to changing circumstances within the network. While challenges remain, the potential benefits of this integration warrant further investigation and resources. Future studies should be geared towards developing new methodologies and hybrid techniques due to the rapid improvements in computing technologies to enhance integrated models scalability and computational efficiency.

6 Practical Implementation of Integrated Models in Mobile Network Capacity Planning

When applied in practice, integrated models involving System Dynamics (SD) and predictive analytics for mobile network capacity planning confront some considerations and challenges. Since the theoretical promises of this hybrid approach are quite apparent, translating these benefits into real-world applications requires careful planning and execution.

An inevitable difficulty concerning the application of combined models is data collection and preprocessing, [10]. Mobile networks and associated datasets can be described as inherently dynamic or heterogeneous systems that include network logs, user behavior records, traffic patterns, and other sources. Such data streams often contain discrepancies, noise, and inconsistencies among measures that must be corrected before they apply for modeling purposes. It is also important to perform efficient data preprocessing, such as data cleaning, data normalization, and data transformation, to maintain the high quality and reliability of the datasets.

Another challenge is incorporating domain knowledge into a formalized structure for an SD model of network dynamics. The comprehension process relies on a thorough knowledge of the system and its parts and includes competencies in SD and predictive analytics methodologies. However, the subjective interpretation of domain knowledge and the complexity of networks in the real world also need help in parameterizing and validating the models. It is paramount that practitioners from the two fields who are competent in these model designs are invited so that the models accurately capture the network dynamics. The confrontation between SD and predictive analytics is another due to the need to assimilate different methodological approaches and data sources. For example, while SD emphasizes the dynamic linkages of variables, most predictive analytics emphasizes the interdependencies between history and statistics. The disparity between the two approaches can be dealt with through hybrid modeling methods that integrate both approaches effectively.

An interesting and quite realistic perspective is to use the recent progress in computing technologies, for example, cloud computing and big data platforms, to improve the integration of the models' scalability and the computational intensity, [11]. Cloud computing platforms like Amazon Web Services (AWS) and Microsoft Azure allow complex simulations to be run, and large volumes of data can be simultaneously analyzed. Apache Spark or other Distributed Computing frameworks help in processing large amounts of data concurrently and hence provide the means of alleviating the computational bottlenecks and scalability issues, [12]. Improvement initiatives using cross-disciplinary collaboration and specialized training approaches are also important in ensuring that the decision-makers and the technical specialists have a standard conceptual model and understanding of the model outputs and network management objectives. Models developed with input from various stakeholders are more practical and contribute to the organization's overall strategic objectives since they are developed with a clear understanding of the technical aspects.

To reduce risks and enhance the confidence of stakeholders in the approach, an incremental implementation strategy can be implemented, starting with a pilot test of the integrated models within certain applicable network regions or use cases. With gradual scale-up, potential challenges can be identified to assist in model refinements before the applications are rolled out to wider network regions. This method enhances the iterative process and enables the models to be active and useful within changing network scenarios.

The combination of models in practice includes addressing problems related to computational complexity and the operational aspect of dynamic network environments. Historical data will likely become outdated and inadequate in predicting the behavior of rapidly changing networks and users. One way to counteract this is to make it a standard practice to periodically revise the integrated models to ensure their continued relevance and effectiveness. This requires permanent accounting, estimating a network's performance, and designing new models and strategies to learn from the incoming data and adjust the models accordingly. Therefore, integrated models' mobile network capacity planning requires thorough planning. However, The difficulties apparent here show benefits worth the strain and further pursuit and investments. Advances in computing technologies, the need for interdisciplinary work, and an incremental approach to implementation should make realizing fully integrated models for the dynamic planning of mobile network capacity possible.

7 Conclusion

Combining System Dynamics (SD) and predictive analytics tools is a substantial mobile network capacity planning innovation. This hybrid approach overcomes the weaknesses of traditional predictive analytics systems by embedding such variables as dynamic feedback loops, stocks, flows, and time delays, which are fundamental for capturing the in-built nonlinearities of mobile networks. While integrating the capabilities of both paradigms, it is possible to construct predictive models that are more robust and adaptive to changing network conditions.

The advantages of this integration are clear. Feedback looped into the predictive models enables the interdependencies of the various components within the network system to be modeled and better future network requirement predictions to be made. The real-time data used makes them applicable even in dynamic network scenarios. Other than that, there are opportunities for improving predictive models, such as hybrid modeling techniques incorporating SD and machine learning or neural networks that can fit historical data, including new evolving data.

Nonetheless, there are still some areas that can be improved upon. One of the significant obstacles in this process is the need to develop and understand models related to mobile networks while coping with their ever-changing dynamic features. At the same time, integrating such models is complex and demanding in terms of computational resources. However, emerging computing technologies like cloud computing and big data platforms can be considered solutions that allow for significantly improved efficiency and scalability of integrated models. Facilitating interdisciplinary collaboration of this kind and incremental implementation strategies should also help address these limitations while ensuring that the models are applied in practice and are useful.

Future studies need to be more centered on constructing novel and hybrid techniques with the assistance of artificial intelligence (AI) and machine learning to enhance SD models. There is also a need to investigate emerging technologies like 5G and the Internet of Things (IoT) further and their effect on network capacity planning. Further development in this area can improve the efficiency of such strategies and dynamic capacity planning in general, improving mobile networks' performance and dependability.

To summarize, combining SD with predictive analytics offers great opportunities for the future of mobile network capacity planning. After overcoming the relevant challenges and benefiting from the advantages of this integrative approach, more fine-tuned and flexible predictive modeling can be constructed to operate effectively within the changing network conditions. This is quite an improvement in the area and can be useful comprehensively for network planners and decision-makers.

References:

[1] N. Sghir, A. Adadi, and M. Lahmer, "Recent advances in predictive learning analytics: A decade systematic review (2012–2022)," *Education and Information Technologies*, vol. 28, no. 7, pp. 8299–8333, 2023.

[2] I. Tomic, E. Bleakley, and P. Ivanis, "Predictive capacity planning for mobile networks—ML supported prediction of network performance and user experience evolution," *Electronics*, vol. 11, no. 4, p. 626, 2022.

[3] N. Darabi and N. Hosseinichimeh, "System dynamics modeling in health and medicine: a systematic literature review," *System Dynamics Review*, vol. 36, no. 1, pp. 29–73, 2020.

[4] B. K. Bala, F. M. Arshad, K. M. Noh, et al., ”System dynamics,” *Modelling and Simulation*, vol. 274, 2017.

[5] J.-W. Jeon, O. Duru, Z. H. Munim, and N. Saeed, ”System dynamics in the predictive analytics of container freight rates,” *Transportation Science*, vol. 55, no. 4, pp. 946–967, 2021.

[6] C. Pupiales, D. Laselva, Q. De Coninck, A. Jain, and I. Demirkol, ”Multi-connectivity in mobile networks: Challenges and benefits,” *IEEE Communications Magazine*, vol. 59, no. 11, pp. 116–122, 2021.

[7] S. Brdar, O. Novovic, N. Grujić, H. González-Vélez, C.-O. Truică, S. Benkner, E. Bajrovic, and A. Papadopoulos, ”Big data processing, analysis and applications in mobile cellular networks,” *High-Performance Modelling and Simulation for Big Data Applications: Selected Results of the COST Action IC1406 cHiPSet*, pp. 163–185, 2019.

[8] M. A. Kamal, H. W. Raza, M. M. Alam, M. M. Su’ud, and A. b. A. B. Sajak, ”Resource allocation schemes for 5G network: A systematic review,” *Sensors*, vol. 21, no. 19, p. 6588, 2021.

[9] J. A. Bastos, ”Forecasting the capacity of mobile networks,” *Telecommunication Systems*, vol. 72, no. 2, pp. 231–242, 2019.

[10] J. Sutherland, I. Townend, Q. Harpham, and G. Pearce, ”From integration to fusion: the challenges ahead,” *Special Publications*, vol. 408, no. 1, pp. 35–54, 2017.

[11] A. K. Sandhu, ”Big data with cloud computing: Discussions and challenges,” *Big Data Mining and Analytics*, vol. 5, no. 1, pp. 32–40, 2021.

[12] F. Aslam, ”Role of cloud computing for big data,” no. September, 2023.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.