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Chapter 3: Implementing intelligent automation and decision-making within telecom networks through advanced machine learning models

3.1 Introduction

This chapter presents decision-making through intelligent automation methods using machine learning models for telecommunications network performance management, allowing for the assurance of quality of service. The proposed models are aimed at anomaly and change point detection to reduce the operational complexity for operators, using an efficient tool of machine learning and network management. The performance evaluation of these techniques is important for demonstrating and comparing the practical advantages in real-time networks. Telecom network operation processes benefit from automated and semi-automated techniques using intelligent algorithms and reliable software. Their capabilities can assist the ever-increasing number of Managed Service Providers that usually cope with the complexity of very large networks with fewer available labor resources. The time and effort to identify poorly performing network segments must be minimized because they can impact revenue and customer satisfaction. Detecting network issues earlier is a clear advantage for the proactive treatment of a network.

Network management in its different layers also supports applications that are running over the data network platforms. Network performance evaluation and management have become more complex and challenging with the use of several quality of service levels and diverse network resources. The idea of intelligent network management is based on the association of machine learning models to optimize the automation of network maintenance processes. These models can efficiently detect anomalies and change points with a lower rate of false alarms. This efficient automation lightweight cycle for the management process can enhance network privacy and quality of telecommunications networks. The simplified strategic argument is that operators can save money by supporting network operations with a minimum number of skilled personnel. Considering the great improvement of machine learning techniques over the last few years, many important problems can be addressed efficiently and reliably.

3.1.1. Scope and Objectives of the Study

Scope of the Study The focus of this paper is to provide an initial view on how machine learning and other relevant techniques could be used to automate operational support activities in emerging software-based telecommunications core infrastructure, focusing mainly on the management of network transport resources. The use of machine learning for operational support activities in telecommunications is quite novel. The management of these services assumes an operator perspective and addresses the need for cost-effective network support systems that optimize telecommunications infrastructure and element capacity. Some real problems are formulated as mathematical programming, linear and/or integer programming. Ways are identified that commercial machine learning tools could be applied to help solve these problems, tested with real-world data, and evaluated critically to propose next steps. The study has an introductory character, which aims to trigger the operators' personnel to ask themselves questions about this business view and, together with data scientists and researchers, open up to a new perspective on the problem. The most interesting point will be around the end, where a few hours will still be spent thinking about the topic and meeting the impacts of the use of some techniques. Treatments could be much more in-depth for all covered topics. When necessary, we have addressed a little of history and definitions. The context of the problem is presented, and we try to associate network elements with mathematical problems. Doubts about the relationship of the variables of our problems with network elements are certainly interesting, and we hope that experiences are shared. With real problems raised from the beginning, we were able to use data and test models. We reiterate the importance of conversations with those who move the real world from big data research. In the end, we identified opportunities.

3.2. Background Information

In this section, we provide foundational and technical details related to the telecommunications industry, and in particular articulate the problem statement, review related work, and advance our thesis that machine learning and AI models can demonstrate significant improvements in network troubleshooting and decision-making.

The telecommunications industry is highly mature and has, over the last couple of decades, seen many key innovations that are indispensable for our day-to-day lives. In particular, mobile telephony is the single largest digital platform that the world has ever seen, with global expenditure surpassing a significant amount in recent years. A cornerstone of organizational stability and growth, mobility is pivotal in achieving the milestones of many innovations to come in the next few years, such as intelligent homes

Fig 3 . 1 : Intelligent Automation with Artificial Intelligence & Machine Learning

and buildings, connected vehicles, augmented reality spaces, and industrial automation with globally connected IoT devices. Despite the advancing frontiers, the telecommunications industry is not free from pains; organizations have been succumbing to the pressing issues of declining ARPU, increasing subscriber churn, network performance, and network modernization. The rising complexity of network infrastructure and geographic coverage has put immense pressure on service providers to achieve operational efficiencies, maintain or exceed customer experience expectations, and, most importantly, stay ahead of the competition. With the ever-expanding scale of the network, it is also increasingly challenging for human experts to quickly understand, diagnose, and respond effectively to customer problems. Ultimately, delivering faultless service can put an unacceptable amount of stress on an organization's human talents. To address these concerns, the telecommunications industry has made significant strides in recent years toward the consolidation and automation of network operations. As systems increasingly rely on machine learning and AI to operate key business processes, it is critical to have validated explanations and contextual interpretations of why the solution model behaves in a certain manner. How an AI interprets business processes is a different question from how we interpret it, but equally important in the context of modern network troubleshooting and maintenance. We conceptualize our approach in case studies for discovering network anomaly interpretation. Proper interpretation will build the foundational trust that is critical for human experts to have confidence in how an organization utilizes and operationalizes models into meaningful automated decisions.

3.2.1. Introduction to Telecommunications Networks

Telecommunication networks are often categorized into two broad classes: fixed-line and wireless. This categorization, though simplistic, is not without its problems. Fixed-line networks, also known as wireline networks, refer to the physical installation of communication infrastructure implemented using a transmission medium, such as coaxial or fiber-optic cables, linking an exchange in a customer's location (Mestres et al., 2017; Foukas et al., 2018; Jiang & Wang, 2021). The network may service universal service obligations, carrying services such as narrowband voice and broadband data communications. Traditional fixed-line networks, at the lower end of the spectrum, can service dial-up and asymmetric digital subscriber line broadband services. At the higher end of the spectrum, fixed-line networks may service symmetric data rates, multiplex of digital subscriber lines, or gigabit passive optical networks. These broadband network technologies can typically support video services such as voice over IP, streamed television, and broadcast television.

In contrast to fixed-line networks, wireless or mobile telecommunications networks offer voice and data communication using a radio link between a base station and a customer location, typically using a handheld cellular mobile phone. Mobility means that voice and data services can be available to users while they are moving. Some competitors in the telecommunications industry are mobile virtual network operators. In some cases, the MVNO is regarded as a self-branded reseller and not as a genuine mobile operator. MVNOs lease network capacity from traditional mobile network operators. They then set their own pricing, billing systems, marketing, and customer service offerings. Public Protection and Disaster Relief business models are also emerging, particularly in light of pandemic diseases. Other examples of mobile networks characterized through business models include, but are not limited to, off-portal machine-to-machine, low-power wide-area network, and unlicensed spectrum networks offering internet access traffic offload from 3G networks.

3.2.2. Evolution of Automation in the Telecommunications Industry

Telecommunications networks have evolved from simple voice and fax offerings provided by traditional telecommunication service providers. These providers have gone through several generational advancements, encompassing six generations of technology, from analog to digital, to the present digital technologies. These generational advancements have brought about revolutionary consumer-direct services like voice over IP, voice over long-term evolution, carrier direct services like virtual routers, domain name servers, virtualized energy equipment, and so forth, provided through network function virtualization and other cloud-based services using software-defined networking. The next generation of connectivity will be delivered through 5G, not only to power mobile phones but also to power the Internet of Things and industrial solutions and applications (Zhang et al., 2019; Tang et al., 2020;).

The service and business models are becoming narrower and broader due to the ever-evolving technology. These technological advancements have made service provider networks increasingly complex. This complexity is compounded by the intense competition that providers face. Additionally, providers need to continuously strive for improvements in quality of service without having a corresponding increase in capital expenses and operational expenses. User experience deteriorates with network congestion and packet loss due to sampled monitoring and KPI trackers, and policy-based orchestration. This has led providers to evolve to what is now called intelligent automation, making decisions to model the network for improved performance over maintaining network performance. This mode of automation is now extended over automated provisioning and lead allocations for sustaining the status quo of the network. The spectrum of these decisions is taken in the zone of constraints, redline policies, and over-threshold measurements. These broadly cover large vistas of machine learning applications.

3.3. Machine Learning in Telecom

Machine learning is the process in which machines learn a series of data by themselves. They create a set of patterns and functions from it. This discipline provides methods, techniques, and tools that can help solve challenging problems, especially when the amount of data available is very large. It encompasses techniques that range from simple unsupervised learning to those that require supervision. In this study, the area of machine learning that mainly functions is unsupervised learning, which allows a system to operate without human interaction and requires no supervision or predefined patterns.

One way to create a machine learning model is to pass a representative amount of data to the model so that it can be trained and, after having it ready, pass another dataset so that it can be tested. After the training phase, the confirmation stage is performed. The training phase represents the process in which the system incorporates the patterns of the data's input parameters but does not learn the exact solutions of the data to be tested, leaving it to discover them on its own. The confirmation phase is when the model is tested with another set of data, usually larger than the first, in order to check if the patterns of data it has learned are correct. The canonical model used in this study is the two-phase batch learning, where it introduces a dataset, trains the network with this dataset, and then tests the model with another dataset, the verification phase represented by RMSE.

3.3.1. Fundamentals of Machine Learning

Intelligent automation and decision-making in telecom networks using machine learning

The aim of this chapter is to provide an introduction and an overview of the various applications of machine learning and intelligent automation in the field of telecom networks for network performance improvement. The chapter provides an introduction to machine learning and then explores the various techniques of machine learning such as supervised learning, unsupervised learning, and reinforcement learning used in diverse network areas such as optimization of wireless communication, intelligent routing and network management, demand forecasting, and many others.

Machine learning refers to the techniques used in computer algorithms to allow computer systems to learn from interactions and other types of observations and data, and to carry out tasks according to those observations. The key objective of machine learning is to understand, design, or emulate intelligent behaviors of computers. It is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead. It also focuses on the development of programs that can teach themselves to grow and change when exposed to new data. The process of machine learning is typified by an expert using existing data or observational experiences to identify patterns and develop predictive models, which can be deployed to generate decisions and knowledge to improve societal conditions.

3.3.2. Types of Machine Learning Models

Machine learning models can be roughly classified into three different types. Based on the type of task being solved, the three types of models are:

• Supervised learning: In supervised learning, the model is trained to map inputs to labeled outputs. In other words, the system is presented with a set of inputs and corresponding outputs, and it has to learn the mapping from inputs to outputs. Once the mapping has been learned, the system can predict the output of new input data. Supervised learning is typically used for regression, where it is asked to estimate the sales or the cost of an item based on input features, and classification, where it tries to predict the discrete value of categorical variables.

• Unsupervised learning: Unsupervised learning deals with finding hidden patterns in the dataset. If there are no labels in the dataset, the model uses only the input data to find the relationship between the items. This can be done by creating clusters from the input data using clustering algorithms, distinguishing the frequency of such clusters by the density-based clustering model, or by using a similarity-preserving map, also known as an autoencoder, among others.

• Reinforcement learning: Reinforcement learning is a hybrid model that behaves as supervised learning for several parts of the training process and as unsupervised learning at other parts. The learner is not told which actions to take, but instead, it must figure this out by a reward given to it after each action. So, the model should have a couple of successful steps, and these steps will be recorded; then the model will try to behave like the successful steps in the future. Reinforcement learning is mostly used for robotics and gaming optimization applications, among others.

3.4. Intelligent Automation

A network must offer continuing user-centric service and high performance and availability while preserving the principle of automation for expense mitigation. The latest network solutions suggest the fusion of cognitive network automation and software programmable systems to fulfill this objective. Under autonomic control, the steps of identification, routing, and recovery are executed, with monitoring and understanding in place to help outline the policy applied to execute the steps. Intelligent automation, comprising machine learning, process-driven automata, and precise strategies in each category of cognitive operations, is what turns an unjust network into a cognitive one. The variety of intelligent automation uses yields raised levels of degree of automation growth, an abiding problem in autonomic networking. We present telecom network tasks and cases based on great coalition technologies standard in the industry.

The maximum portion of telecom networks typically reserves faults mostly in the data layer cluster that absorbs device action to recover services available to both IT and analytics flaws in a given condition. Intelligent automation can sometimes do this through a cognitive control loop that can identify, inform, and generate practical recovery actions for service delivery within a covert reaction time, without network traffic delay at any juncture, altering negative services to consumers. Much like a living organism, this management and implementation are found to be cognitive on behalf of being there, assigned with the responsibility of taking care.

3.4.1. Definition and Importance

What is Intelligent Automation? Automation is a process that minimizes human intervention, thereby minimizing errors and improving efficiency. If, when needed, automation also has the ability for decision-making, it is Intelligent Automation. More often, machines perform this task in the form of a software bot or a robot. Multiple bots coordinate with each other, or with humans, to perform complex activities. When a combination of both automation and artificial intelligence and machine learning are used together, it becomes Intelligent Automation with decision-making. Playing games and decision-making in routing were some of the early applications of AI techniques. In the last six decades, there have been both setbacks and tremendous progress via optimization in automating various systems. Intelligent automation and decision-making in telecom networks is still a new application area.

An important function of decision-making occurs when a special set of tasks decides about future operations. Those that can easily be defined with exception report analyses are handed over to occasional involvement by higher decision levels. In practice, therefore, vital business functions requiring complex and fast decision-making reporting systems are retained with the ultimate management levels. Correct and fast situational awareness is of great importance in telecom networks. The behavior of various network entities in adverse conditions has to be taken into consideration while making decisions. Human knowledge processing using machine learning has great potential to replicate this behavior and evolve superior models. AI can automate such activities in critical situations, ensuring that human intervention is minimized, contributing to the goal of 'Zero Touch Networks.'

3.4.2. Benefits of Automation in Telecom

Telecommunications networks are being automated to increase the efficiency of network management. Automation can reduce the time and cost needed to launch a network service, improve network reliability, proactively predict faults and take appropriate action to minimize the impact of the fault. Network automation uses software on a network to help it operate efficiently. The automation software captures information, analyzes the data, and provides options to allow network components to make decisions without a human operator. The benefits of automation include the reduction of time to market, improved operational efficiency by reducing the number of people required, and a sustainable competitive advantage by providing a high customer experience. Networks are complex systems with high dynamics, uncertainty, and complexity. Network traffic has a high degree of variability. The approach involves using intelligent software to support system operators by providing decision support and preferred actions for consideration. This feature enables the operator to have the best situational awareness and visibility of network and software operations. With efficient automation, the telecommunications network is continuously monitored and optimized to support a growing number of users for communications and the high data rate associated with video, graphics, and gaming applications.

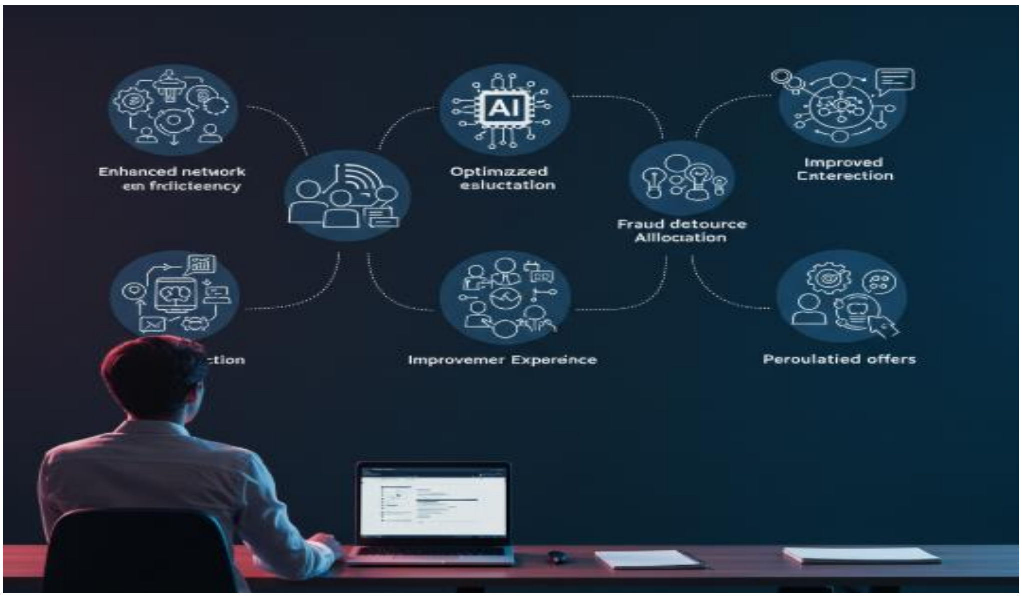

Fig 3 . 2 : AI in Telecom Benefits

3.5. Decision-Making Processes

Let's focus on a decision-making process in general. Decision making is a critical activity in any business process that is framed by the decision-making process and strategy for selecting an alternative solution. Since the decision-making process is commonly dependent on sensing signals or objects embedded within datasets, decision-making can also be solved as supervised learning tasks. In formal decision-making theory, the choice is derived from the theory of actions and decision strategies. The choice can also be grouped into routine and non-routine problems.

The essential components in a decision model are clear objectives, defined alternatives, and projected results of each alternative. Given an option model and various conceivable choices, an objective, consistent, and well-organized decision-making process will be able to assist in justifying an eminent final decision. Techniques for building decision models and for making decisions based on the models have been proposed, and many of them are popular and productive. Nonetheless, when additional, fresh sources of data become more attainable and available to decision makers, and are utilized to make data-driven decisions, our decision-making processes may evolve into fundamentally more complex tasks. With the beginning of a data-driven paradigm, we can start categorizing historical decision data, find new statistical patterns indicating a successful decision, and exploit them to improve decision-making.

3.5.1. Role of Decision Making in Telecom Operations

The area of decision-making covers several functions such as determining investment decisions, type of network, technology, capacity expansion, traffic forecasting, workforce planning, labor scheduling, network and service management procedures, service level guarantees, service fees, network security levels, and whether network mergers are beneficial. The quality of company performance in this set of functions can also lead to the success or failure of the organization. Past research explores the application of several techniques to address various challenges in telecommunications. Network design models are heavily influenced by the growth in demand for telephone access services. Modeling assumptions tend to focus on forecast estimates for economic demand for services, as well as population and area growth rates. Business intelligence solutions based on neural networks are analyzed to improve customer retention and the lab deployment algorithm. Other types of business intelligence are used to derive the optimal design of services, network design, or the framework for reinforcing market solutions to take advantage of new internet services. Research is expanding and examines the role of machine learning methods to improve the decision-making process, and new challenges are motivated by the deployment of a 5G communication network powered by the cloud. Since the wired and wireless communications sectors are evolving and growing in importance, decision-making can not only solve conventional challenges but also address the implications of new directions from emerging technologies. Topics such as economic decomposition in the pricing of telecommunications services, public perception, electronic communications, standardization procedures for Long Term Evolution, traffic classification, regulatory centralization, and ubiquitous communication services exemplify the variety of challenges to which decision-making techniques can provide answers for researchers and stakeholders in the telecom area.

3.5.2. Integrating Machine Learning with Decision Making

Intelligent Automation and Decision-Making in Telecom Networks Using Machine Learning

1. Implementing Intelligent Automation for End-to-End Network Optimization

2. Integrating Machine Learning with Decision Making

3. Enhancing Learning Algorithms Using Additional Technologies

4. Strategies for AI and Cognitive Computing

Integrating Machine Learning with Decision Making

Based on the probability, precision, and F1 score, which are conventionally used standard metrics to measure the performance of machine learning models, different combinations of the machine learning prediction and the decision are developed for the training dataset models: Decision Rule Emo B-D Token LR TF-IDF, which is the tokenization method along with the linear regression; Decision Rule Emo B-D TF-IDF SVC and Decision Rule Emo B-D TF-IDF KNN, which are k nearest neighbors; Decision Rule Emo B-D TF-IDF LR and Decision Rule Emo B-D TF-IDF RF, which are the random forest; the combination of the text vectorization method without the tokenization and the linear regression; the combination of the text vectorization method without the tokenization and the k nearest neighbor; and the combination of the text vectorization without the tokenization along with the SVC. Each model identifies the probability that a certain decision category leads to both models, then identifies the result—model prediction and system decision for the current and for all the participants.

3.6. Advanced Machine Learning Techniques

The shallow machine learning models are usually used in practice. The main reason is that the data available for modeling is specific to the data used. The sophisticated and deep machine learning models with many hyperparameters do not work well generally because their results are not consistent and they can be overfit. These models have too many hyperparameters which make them too sensitive to fluctuations and do not work well in the test phase. For optimal allocation of spectrum, considering QoS requirements in the long term, this might be acceptable as the cost is warranted by the level of QoS provision to maintain CAC compliance.

One way around these problems is to take an aspirational approach using a data-driven feedback tool to provide a level of QoE longer-term prediction, rather than to directly model the full complexity of the QoE-C QoE relationship. To achieve this, we developed an RNN to model the observed tracking performance over time. With the current project, we are investigating a proof-of-concept system that captures QoE application traffic flow characteristics at multiple choke points within the network and uses a MAP to estimate in real-time the application QoE as the traffic flow progresses through the network. We provide initial validation experiments that show MAP is capable of accurately modeling the QoE in real-time over specific traffic paths. Data-driven methods have the drawback of requiring large amounts of training data. Event and application data from a production network, which typically involves scoring to interpret, could be used to enhance learning output.

3.6.1. Supervised Learning

Supervised learning involves learning that maps from inputs to outputs based on input-output pairs. Despite the fact that we are motivated by problem description and the kind of input and output pairs that are used to train the model, the identical terminology is used universally. Three steps are involved in a typical supervised learning situation. First, the model form is chosen. This form might make use of linear or nonlinear components, as is the case with the linear combination of functions. Two parameters that distinguish one model from another are the dimensionality of the input and the output.

Next, the model's parameters are found by comparing model outputs to the outputs from historical data. This enables the model to minimize its prediction mistakes. Presenting the model with historical data allows the model to learn. Finally, to evaluate the efficacy of the trained model, a separation of historical data is used to validate the model. These guidelines for validation will enable a trained model to offer reasonable predictions on data that is not included in the training data set. Any discrepancies between the model's predictions and the observed historical outcomes are referred to as loss. Hence, supervised learning also entails minimizing such a loss.

3.6.2. Unsupervised Learning

The telecommunication industry is an ever-evolving multi-service and multi-technology landscape. The blended services and complex technologies used to deliver these services mean rapidly increasing complexity as the time-honored concept of network silos ceases to exist. This ever-increasing complexity of physical and virtual resources and associated services, continuous changes, security threats, and customer expectations make the autonomous operation of the telecom network an attractive grand challenge for the application of artificial intelligence, and specifically machine learning. In unsupervised learning, an autonomous system selects input features from a large number of unlabeled examples on its own and tries to group or identify similar examples.

This chapter overviews the application of unsupervised learning for IO, mainly fault detection, predictive maintenance, fault propagation, and forensic analysis. The unsupervised learning discussed includes principal component analysis, K-means, self-organizing maps, DBSCAN, isotonic regression, and tensor decomposition. In particular, the growing interest in applying unsupervised and semi-supervised learning to the network domain is discussed in light of the immature nature of most unsupervised learning methods in network management. The main challenge of unsupervised learning is the need to define and select the output formats as precisely as possible and not in a vague manner before the algorithm is deployed.

3.6.3. Reinforcement Learning

Reinforcement learning (RL) is a subfield of machine learning that inherently uses a framework of an intelligent agent interacting with an environment in order to optimize a performance measure. A cumulative reward captures the quality of policies that the agent learns. While policies can be deterministic or stochastic, considered approaches usually deal with a stochastic policy. In this context, exploiting the sequential decision process, the exploration vs. exploitation dilemma, dealing with a delayed reward, credit assignment, using a model, and more possibilities emerged as typical and widely studied RL problems. A policy may return for each state a selection probability for each reachable action; on the other hand, it may return a recommendation of a particular action, which has to be selected by some exploration strategy.

Reinforcement learning figures as an appealing computational model well adapted to practical aspects of learning, including learning from few data. RL naturally incorporates the sequential aspect of the decision process faced by the agent. Telecom networks in relation to other ICT sectors are abundantly described and are the target of a great modeling effort. Furthermore, the tangible impact of network and service management enhanced by RL is frequently reviewed and presented. Yet, currently available RL telecommunications applications may require more training data than what can be captured by the network before adapting to various unpredictable and constantly changing conditions.

3.7. Implementation Strategies

This chapter talks about the points to consider when using machine learning-equipped intelligent automation and decision-making tools in telecom networks. The chapter begins by describing the reasons for bringing flexibility into these areas. It goes on to speak about the industry constraints that need to be kept in mind while deploying tools in telecom core networks, and then moves to a phase-wise approach to deployment and testing of machine learning-equipped approaches, and concludes by mentioning the need for creating a common real-world data library and an awareness on the part of the field engineers to take the whole process from POC to the definitive stage.

The networking industry is witnessing major transitions, from hardware-based physical devices to more virtual, lightweight underlay infrastructure, with more emphasis on software-based intelligent automation for operational tasks. The use of real network data, big data, is gaining importance in adapting existing tools or in proposing new innovative solutions relating to performance prediction, capacity planning, load balancing, root cause analysis, and adaptation. However, there is still cautious widespread skepticism attached to taking POC tools to a definitive stage, deployment constraints, and operational aspects. The different symbiotic constraints between the developed solution and the real installed base of a telecom company necessitate a well-rounded approach during the POC phase itself. A set of well-defined sufficient necessary conditions, states, and boundaries limit the capabilities of deployed tools. The legacy physical telecom networks have undergone a smooth transformation to depend on intelligent automation decision-making tools. A sound method can be adopted by the industry to deploy machine learning-equipped tools such that the telecom service is not affected unnecessarily. Furthermore, a common data repository can foster the development of industry-grade tools and foster a different mindset among the field engineers.

3.7.1. Data Collection and Preparation

Data collection, cleansing, and storing are the fundamental processes in machine learning. AI algorithms need multiple levels of data sources to be trained properly to perform specific tasks and achieve intended outcomes. However, certain tasks often need to propagate damaged data dependencies, which can change data in order to be trained with new features generated. We will use the data that are required according to the business application use cases. This data might need to be adjusted to facilitate the application of specific ML models that introduce tasks to process and analyze large and varied datasets. We then must point out the way to obtain that data with the desired frequency. Lastly, it will require points of storage and ensure that the models are continually upgraded and monitored. This service provides the organization with the ability to facilitate the ML model creation by using any type of data sources.

3.7.2. Model Training and Validation

Deep learning algorithms require extensive databases for training. The quality of the training depends on the amount of diverse and validated data. Rigorous validation and careful data preprocessing play a crucial role in assessing the integrity of the model. Poor quality training data impacts the reliability and robustness of the model. The dataset needs to be validated, ensuring that it spans the range of conditions present in the system of interest. In some classification models, the major class must be restricted and the minor class increased to achieve a balanced classification model. In a predictive model, the data cannot be either underrepresented or oversampled. The neural network should be validated using suitable methods. The data used to tune the hyperparameters of models must be separate from the validation set. The validation process should ideally be done with access to an additional dataset that it did not encounter during the training phase. A neural network architecture with a larger size, defined as the stacking of more hidden neurons or layers, is essential for better learning and achieving the required prediction accuracy.

3.7.3. Deployment in Telecom Networks

Telecom Cloud can be a typical environment for all the functionalities discussed earlier for intelligent automation and advanced decision-making in telecom networks. Telecom networks have become so complex and have been developed so much that they could be seen as real cloud data centers. They are dynamic and have a lot of functionalities, despite the fact that the applications that run on them are telecommunications services which are long-lasting. As such, the insanity of development in telecom networks is actual today. In time, the cost of these networks becomes very high compared to the earnings potential of a service that only works for months, and the network capacity that runs the service is not always sufficient for the service to work with good quality.

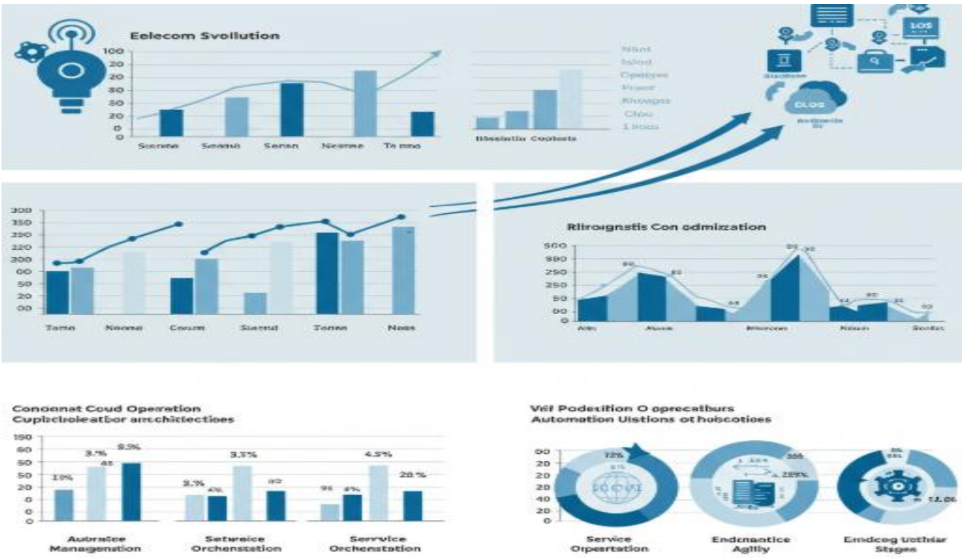

Fig 3 . 3 : Telecom Cloud Evolution: TCO Breakdown vs Automation Opportunity (2020 - 2025)

Each Network Function is self-managed and has proactive repair, capacity, and demand management. Manually intervening and the fact that different algorithms to manage traditional SDN and/or 5G signaling and optical redundancy introduce two aspects. First, it increases the TCO of the network as skilled people cannot get efficient management and cost allocation, and even after a network has been built or upgraded, skilled intervention cannot be omitted because it is necessary to resolve dynamic service contention with priority, cost, and effectiveness. Secondly, both of these aspects make it increasingly difficult to manage the services provided to people with SLAs and SLOs. The services become too numerous, too varied, too personalized or have a management intervention which has been too fine-tuned and therefore costly with respect to the benefit provided to the customer or to the communication network operator.

3.8. Conclusion

The concluding chapter provides insight and understanding of the future applications of machine learning in the telecommunications area, where the primary focus is on network operation and management. The explicit intent of this chapter is to contribute to the understanding of the key properties of data, as well as algorithmic, system, design, and policy challenges in practical settings and decisions that bear on the real-world application of these technologies. Additionally, we provide the latest advancements on the topic by identifying the gaps in the literature, and then we extend the research horizon by proposing open research questions. The data presented in this chapter are extracted from research studies focusing on machine learning applications in the telecommunications area.

In practice, a new generation of smart wireless networks is bound to carry out real-time, fine-grained, and predictive intelligent automation in order to provide satisfactory services to the very diverse and vast number of emerging applications. To achieve such a complicated objective, machine learning definitely needs to be a fundamental part of the methodology. This is due to the fact that machine learning has demonstrated its ability to perform well in making decisions based on large and heterogeneous data, and in handling complex interdependencies between input and output that are difficult to be precisely mapped theoretically. In this chapter, after concisely introducing the background, we provide an overview of the data-driven or learning-based telecommunications area. We then dig into the details of modeling, optimization, and learning techniques that are applicable in such an area. Finally, we conclude the chapter with several open issues that merit future study. Overall, our aim is to sketch out and shed some light on this promising area of research.

3.8.1. Key Takeaways and Future Directions

With intelligent automation, operations staff at India's largest mobile service provider can support individual cell tower upgrades with one to two prototypes per-cell intelligent features. The tower installation must only provide power, data and access to the prototype by mounting the prototype on the side of the control cabinet at a height suitable for mobile cell installation and without exchanging parts or data. The target has 25% installation completion within 2 years. After identifying the most feasible prototype use cases for direct impact on profit margins over a short period of time, the operations team selects a prototype with the functionality to enable operators to learn the basics of the intelligent automation process through the case in more detail. Review.

While waiting for the full outcome of the task, the research team subsequently launched an AI system in cellular network design that leverages a variety of machine learning approaches. Consider the learning experience achieved with the prototype. After finalizing the use of the prototype, realizing its function and ultimate high return, the team explores 8 possible general routes of AI use and leans to mature and extend the philosophy and practical guidelines of the AI cell network widening. This impacts almost the entire macro- and micro-level decision-making of the cell tower in its life cycle.

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