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Leveraging Artificial Intelligence to Improve Quality of Service in Next-Generation Broadband Networks

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Abstract

In recent years, Operators are confronted with new challenges regarding the Quality of Service (QoS) they provide to their users. Changes on the traffic load after the emergence of smartphones and other mobile devices with capacity for using real-time applications have produced an overloading excess of many mobile networks. New paradigms such as the Internet of Things (IoT) and Smart Cities are expected to generate a massive traffic growth that current fixed and mobile networks may be unable to support. In addition to this, the quality of service perceived by the users is becoming the most important selection criterion in the choice of the service provider. Providers need an exhaustive management of the Internet Protocol (IP)-based services that they offer, and specifically, of the related QoS parameters. A joint approach is proposed to leverage Artificial Intelligence (AI) techniques to achieve an accurate monitoring of QoS parameters that impact on user experience. Data imported from the provider, application and content server domains enables to train Random Forest, Support Vector Machine and Decision Tree models, which are used to predict target QoS parameters values. A congestion classifies conditions of the multimedia content targeting. An extensible framework for dynamic managing of the QoS of the services offered is provided. Monitoring tools. QoS Monitoring Framework is devised for "on-the-fly" monitoring QoS controlling of usage by classifiers and models. Classifications of the IP-based services offered are needed and relevance of the parameters is estimated to identify targets for applying those policies. A clear approach should be defined on the policies available in the context of controlling the service provisioning ("active"), specification of the QoS to achieve ("passive"). A framework for evolving the adequate policy actions according to the usage of the services is required. Ensuring that customers experience a certain level of QoS has become an important issue in the design considerations of networks. To achieve this goal, it is important to identify those parameters that need to be controlled and those that impact on the customer perceived service QoE.

Keywords: Artificial intelligence, quality of service (QoS), next-generation broadband networks, AI-driven network optimization, machine learning in telecom, broadband performance enhancement, intelligent traffic management, network automation, predictive analytics, service reliability, dynamic bandwidth allocation, low-latency networks, intelligent fault detection, cognitive networking, AI-based resource allocation, 5G networks, network resilience, data-driven decision making, self-optimizing networks, telecom innovation.

1. Introduction

Broadband Internet is one of the hottest topics in the engaged society, and research on broadband Internet is on the cutting edge of ubiquitous multimedia communications. It is enjoyed by the broadband multimedia services such as Video on Demand (VoD), Internet Protocol television (IPTV), and video conferencing etc. [2]. However, such services are beyond the easy provision alongside traditionally encapsulated services. The main issue is how to guarantee a genuinely 'wide' band in the high-performance broadband IP networks and provide different level classes of broadband multimedia services. Meanwhile, quality assurance is required for even provisioning of such services, together with service delivery. This implies that traffic characterisation, modelling and analysis, network calibration and planning, and the design and implementation of network protocols should be on the basis of broadband multimedia service generic modelling. The ongoing scenario of discovering integrated broadband multimedia services, however, presents various hurdles yet to be resolved. To provision different level classes of broadband IP services, it is required to ensure network quality of service (QoS) though the broadband IP network's natural best-effort service may not be compatible with this requirement [1]. Quality judgement is referred to as quality assurance in service provision. Quality assurance is required to embrace both perceptual quality of experience (QoE) issues as well as technology-dependant quality of service (QoS) assurance issues transparently across the entire end to end delivery chain to guarantee a genuinely quality assured service. Technologies for per-service, per-network, and per-domain quality assurance, such as network engineering, QoS and QoE monitoring, control mechanisms, negotiations and settlements, and quality modelling and prediction, have been researched independently. The combination of all kinds of such technologies and the resultant multi-headed monster hindering easy inter-operation has become a big headache for telecom service providers. Moreover, as end-to-end quality can only be assured by end-to-end control, these different quality assurance technologies cannot be separately designed, but rather need to be by taking into account the mutual impact between the different quality assurance technologies on each of QoE and QoS. In light of this, a user-perceived quality aware technology-agnostic service agnostic multi-platform quality assurance approach design paradigm against existing engineering based approaches to telecom service quality assurance is proposed.

2. Overview of Next-Generation Broadband Networks

Broadband services are technologies that provide high-speed Internet access by means of asymmetric digital subscriber line, fiber to the home, dedicated data line, and vendor proprietary wide area network. Next-generation broadband networks are a higher level of broadband networks with service networks including next-generation packet switched network and next-gen circuit switched network and finally accompanying applications networks including next-generation service networks and next-generation content networks. Defining next-generation broadband networks can be simplified by listing its parameters: 1, with carriers conducting network services, data, wireless, and voice on the same network, next-generation packet switched nodes are required to swap not only diverse types of systems and network packets but also protocol formats across network operators and types in a more intelligent way; 2, with transmission taken over from copper to fiber with homogeneous kinds of transmission in each area of operator infrastructure, next-generation content networks are required to exchange contents among network operators; 3, with the technology for service added to network enhanced services, the inclusion of services in network is required and thus network service operators or NSOs are introduced.

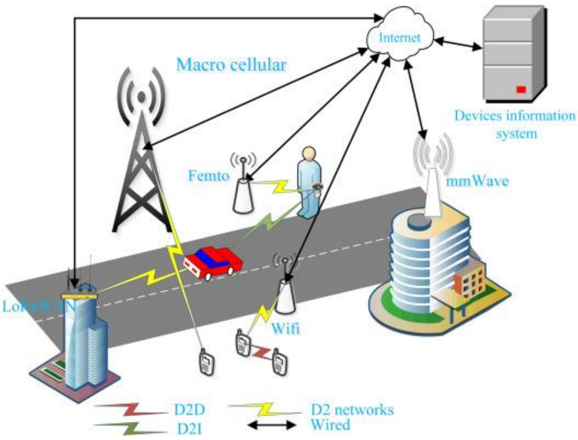

Fig 1: Next Generation Networks

Next-generation broadband service networks are expected to support a variety of upcoming applications such as High Definition Television and new services built on future Internet in addition to the supportive capability of current applications in broadband service networks. Quality of Service is a combination of provisioned traffic parameter, validated parameters, and assurance of parameters. Broadly, quality parameters of network connections can be classified as packet loss, delay or jitter, and those affecting a connection are bandwidth, buffer size, and service scheduling. Next-generation QoS has the challenges of service level agreement and over-provisioning. Different domain's resource management of next-generation QoS is classified as bandwidth broker based inter-domain management and policy based inter-domain management. For a multi-carrier policy independent and aware inter-domain resource management architecture is presented. BB based QoS architecture is evolutionarily stepwise and policy based QoS architecture is fundamentally across different domains.

Next generation networks are primarily driven by convergence of telecommunications and computing. This results in globalization of information transfer and knowledge creation. Telecommunication industry provides broadband access to infrastructure, platforms, and networks. Such infrastructure gives rise to convergence of telecommunications and computing. Such convergence results in a highly competitive business environment for making communication networks more effective at low cost. Thus, enormous quantities of knowledge and information are generated across the globe. It is therefore imperative for service providers to analyze the content profiles quietly and intelligently and supply required information to end users on demand in text and image formats speedily. Hence working closely with telecommunication engineers and scientists, computer and information engineers and scientists must run sophisticated programs to design systems, networks, protocols, and algorithms to respond to the pressing demands of massive data transfer.

2.1. Definition and Characteristics

Quality of Service (QoS) is a critical concept in telecommunications and computer networks that refers to the overall performance of a network or service in terms of its ability to meet certain predefined service-level agreements (SLAs). SLAs are contracts between service providers and clients that define a set of service parameters, like latency, bandwidth, and packet loss. QoS involves the measurement and monitoring of these parameters to evaluate network/service

performance against the SLAs [2]. Effective QoS management allows better allocation of network resources by providing tools for efficient SLA verification and management. This process constitutes QoS evaluation, one of the main QoS management functions. Since the start of Internet, Service Providers (ISP) have seen the need to provide users' traffic different treatments defined by agreements between ISP and customers [1]. QoS management allows better allocation of network resources by providing tools for efficient SLA verification and management, which constitute QoS evaluation, one of the main QoS management functions.
QoS awareness and management tasks require deep understanding of the offered and perceived QoS, but knowledge about those values is not sufficient, as SLA violations may require larger time scales for detection. Provided indicators may be not precise, concerned about whether the indicators pertain to violation or not, which renders mostly unavailable the source of the violation or degradation. Telecommunication networks produce large amounts of traffic data that describes significant important features. The use of large real traffic datasets allows optimization of the network infrastructure, provide better QoS/QoE experience, and operational efficiency improvements. Exploiting this traffic data is crucial for better management of QoS and SLA on both the network and service side of the Internet. Network Resource Planning may use traffic predictions for physical network upgrades, and a better convergence time is possible if the next best actions are predicted in case of anomalies. QoE objectives for client traffic can be used for application resource allocation. Volumetric approaches to traffic classification with one minute granularity are straight-forward and extremely useful for SLA assurance. Anomaly detection methods are also investigated for tighter abuse-fraud detection models.

2.2. Current Trends and Developments

The emergence of 5G and beyond networks has unveiled a new era of connectedness—an era envisaged to provide connectivity to a myriad of devices, applications, and services. Future wireless networks are expected to support a multitude of services with drastically different requirements: low-latency and ultra-reliable services; massive and sporadic services; and broadband and high capacity services [3]. In this context, the initial service scenarios defined for 5G networks can be classified into three main use case categories: Enhanced Mobile Broadband (eMBB) that targets the need for services with high data rates and low latency, Ultra-Reliable and Low-latency Communications (uRLLC) that is tailored for ultra-reliable and low-latency services, and massive Machine Type Communications (mMTC) for services with a large number of devices transmitting sporadically with low-power levels.
Next-generation network services can have radically different qualities. Next-generation core networks are expected to serve heterogeneous devices with drastically different quality of service (QoS) demands, either within the same service type, or even within the same service sector. For instance, a highly reliable and low-latency network is needed for rapid message transfer between connected vehicles in an intelligent transport system, whereas the same infrastructure should serve users with a very high quality video streaming or mobile applications. In next-generation mobile broadband access networks, 5G and beyond networks are expected to accommodate diverse use cases in a common infrastructure. These diverse use cases generate heterogeneous traffic to be transported by the same network. The heterogeneous characteristics of the traffic lead to diverse performance requirements for the access network linkage. As a result, each service type could have a different required combination of throughput, delay, jitter, and packet drop probability.
In this context, resource efficiency is paramount. Next-generation networks are envisioned to be much denser and more pervasive, which raises more challenges in terms of resource allocation, deployment, and operational maintenance. Future networks should also be more reliable and robust, i.e., able to handle unforeseen events, change of topologies, changes in traffic demands, and route failures. Reliability is also crucial as it is required to reduce the number of dropped packets. The approach taken by 5G networks for Radio Access Network slicing is likely needed in Cloud Radio Access Networks, which rely on a tight coordination of network function placement across different technologies at low-level transport, control, and service layers. In this regard, Resource Management techniques must be designed to keep the desired performance for each slice and to reduce interslice interference to meet service-level agreements. 6G networks must accommodate these requirements by employing efficient resource management techniques; in this context, artificial intelligence and machine learning algorithms are promising tools for achieving network efficiency and meeting the demands of different services.

3. The Role of Artificial Intelligence in Telecommunications

Artificial Intelligence (AI) is populated by various subfields, including artificial neural networks (ANN), fuzzy logic systems, expert systems, game theory, Bayesian methods, the theory of evolution, genetic algorithms, and evolutionary computation. Application areas for these methods are diverse and include intelligent transportation systems, astronomy, medicine, robotics, earth sciences, and, last but not least, telecommunications [4]. All the segments of the telecommunication market, like telephony, mobile communications, and data communications, perform transmission, switching, and routing functions. For the analysis, design, planning, management, and operation of telecommunication networks, practitioners have to develop design and operation methodologies that account for complex and dynamically changing processes, with uncertain and/or incomplete information associated with huge datasets. The geometrical

complexity of the network topology and the substantial number of network nodes call for smart methodologies capable of extracting, handling, and preserving the resources of the network.
Contrary to the widely held belief that AI is only of use and vital in the area of data and/or network security, AI techniques enable the analysis of how network structure and parameters affect the oscillatory behavior of the system. Time-stamped data, revealing what actions were done and what actions succeeded/failed, can be used to create the AI agent that will automatically optimize entity-directed settings. Due to the complexity of the processes, such an analysis cannot be done using classical techniques. Graph theory tools can support classical strategies in ongoing structures, but these tools cannot handle the data explosion in high-dimensional spaces. Due to a small number of nonlinear dynamics, the nonlinear Schrodinger equation (NLS) has been extensively researched for thousands of years.
AI-based techniques are of utmost importance for network functioning, resilience, protection, management, ensuring service quality, and other processes as well. Switches, routers, and gateways play crucial roles in telecommunications systems and are often regarded as intelligent devices designed to take network operational decisions. Without pre-existing models of these networks, AI-based methodologies, especially those for reinforcement learning, can be applied to learn how to perform control tasks through repeated interaction with a dynamic environment, hence taking desirable actions to optimize network performance.

3.1. AI Technologies in Network Management

Next-generation network management may leverage artificial intelligence (AI) technologies in different ways. These techniques discern patterns in operational or experimental data, providing insights into the general behavior of a system. AI techniques differ in the amount of data necessary for training and understanding the phenomena or tasks of interest. A previous review paper categorized AI techniques for network management into five classes: (I) Mathematically-Based AI, (II) Rule-Based Systems, (III) Knowledge-Based Systems, (IV) Sampling or Optimization Techniques, and (V) Learning-Based (Supervised, Unsupervised, Reinforcement Learning).
Data-driven network management approaches prevalent in the past decade automate operational tasks in telecommunications networks and generate a massive amount of raw data. These data can yield insights into the general behavior of systems and processes to enhance service provisioning and operations further. To actually extract relevant insights from data, sophisticated data analysis techniques—dubbed artificial intelligence (AI)—have gained momentum in telecommunications. This study extends the previous mapping of AI techniques against network management tasks by combining results from the first and second phases of USP E2. The basis to build on is (I) Mathematically-Based AI, (II) Rule-Based Systems, (III) Knowledge-Based Systems, (IV) Sampling or Optimization Techniques, and (V) Learning-Based (Supervised, Unsupervised, Reinforcement Learning). AI can benefit next-generation broadband networks in various ways. These contributions can be grouped into three categories.
Network elements, links, and services are still inherently heterogeneous; appropriate methods for AI integration and hybridization will provide benefits for these approaches in next-generation broadband networks. To-Do Loop Network closure and customization nodes would spread across the network and attempt to learn the benefit of the different routing paths available through trial-and-error. Each To-Do Loop would task an architecture agent to modify its configuration based on lower-level learning agents that would optimize rules at only certain timescales.

3.2. Machine Learning for Predictive Analytics

Machine learning (ML) provides a methodology for predictive systems, meaning systems that can, based on the early observation of the network state, evaluate and estimate outputs not yet observable. In context of the wireless mobile networks, this means systems estimating QoS measures that are not yet known [5]. Thus, instead of cohort behavior, networks become proactive to sustain a specific requirement. In the following, maximum throughput prediction will be examined, as a possible approach to enhance the QoE of prolonged streaming or HD mapping applications. The entire workflow is discussed highlighting aspects like detailed sampling procedures, the analysis of the dataset characteristics, the effects of splits in the results, but also details as the newly defined sampling of added measures during runtime. Reliable and trusted models need to face challenges during their lifecycle. The knowledge available and how that knowledge is derived is discussed.
ML has become ubiquitous in the last years, providing a general understanding of the world in a rich and precise way, based on data. The rapid growth of interest in ML is a reflection of its successes across a variety of industries, including drug discovery, marketing, and manufacturing [6]. In brief, the ‘goal’ of ML techniques is to seek a function that takes as input a set of measured properties describing a condition w and provides as output a set of labels a that can derive the current condition. In this manner, they can retrieve the label a based on previously unseen values of measurements w. This method is also called supervised or mediated learning, where the supervised part describes the approach to label the measurements w, and the mediated part describes the mechanics of retrieving the label a. In the broader view, it can be divided into two parts: the first is to decide ON “WHAT” to measure a given condition, to retrieve the label a using ML after building the knowledge. The second, the approach ON “HOW” to retrieve that knowledge.

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4. Quality of Service (QoS) Metrics

QoS is the quality of a customer's experience when conducting a particular service on the Internet. There are multiple domains in which QoS should be assessed. Network-based evaluations measure broadband speed and latency, while application-based evaluations measure service-specific quality. It is best to have combined and validated solutions that map network conditions to service-specific QoS [1]. It is well known that the alteration of network-level QoS metrics affects service-specific QoS-RC mappings. A service-specific QoS metric is much more efficient than analyzing dozens of network quality metrics to determine the responsiveness of service quality. This paper summarized a method for automating the selection of a small data set of network-level QoS metrics that mitigate service-specific QoS impairment. Several optimization criteria can be chosen, including but not limited to the minimization of QoS impairing conditions. Internet access providers are required to take preventive and corrective measures to ensure that the parameters of the service level agreement (SLA) are met. Monitoring solutions are used to ensure that delivered performance matches the committed level since it is understood that a low level of service may cause customers to migrate to competitors or even make a complaint to Government Regulatory Agencies. However, to date, there are not any suitable QoE monitoring solutions for ISPs, which is a considerable challenge, since the problem becomes more critical and complex as users demand new multimedia services, such as Voice over IP, Internet Protocol Television (IPTV), Virtual Reality (VR), and cloud gaming solutions [7]. Network equipment manufacturers sometimes develop techniques for monitoring QoS, but these techniques are limited to the physical and datalink layers. A deeper understanding of network problems in current networks—from packet drops to service-specific performance degradation—is needed.

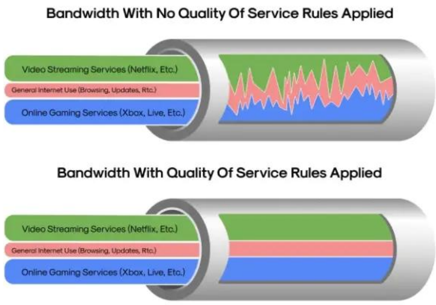

Fig 2: A Comprehensive Guide to Quality of Service: Demystifying QoS

4.1. Defining QoS in Broadband Networks

Over the past two decades, with the introduction of bandwidth-hungry applications, broadband networks have expanded significantly. The next-generation broadband network is expected to be more intelligent in terms of management and service delivery, and AI will play a critical role in this endeavor. These AI technologies will help improve the overall Quality of Service (QoS) offered by broadband networks and, consequently, the overall quality of experience perceived by users [2]. In this manner, delivering higher QoS will result in improved QoE. However, with the presence of challenging environments and new types of applications, providing QoS assurances in next-generation broadband networks will be a great challenge. With the increased complexity of the QoS management problem, AI techniques will help make efficient decisions on resource allocation in real-time. The objective of this section is to provide a brief discussion of QoS and related issues in broadband networks.

The network's ability to handle data flows in a way that guarantees minimum bandwidth and other communication characteristics is known as QoS. The importance of QoS is mainly network-level performance. QoS is the ability of a network to provide better service to selected network traffic over various technologies. A differentiated level of service is needed for networking protocols, which can range from high-priority to low-priority. QoS provisioned networks must perform the following tasks: (1) specify the levels of QoS to be delivered; (2) assess the QoS supplied to the flows; (3) perform admission control; (4) allocate network resources accordingly; (5) apply mechanisms for further traffic conditioning; and (6) choose the routing and forwarding of the flows.

The delivery of real-time multimedia applications such as Voice over IP (VoIP) requires guarantees of some form regarding their QoS. Traffic management is one of the facilities of a broadband network that is typically considered by service providers. It comes into effect once an existing connection enters the network. Traffic management techniques help to assure that QoS levels are satisfied within a domain. One of the earliest applications of the Service Level Specification (SLS) is the definition of the network's different levels of services in terms of SLA and Service Level Agreement (SLA).

4.2. Key Performance Indicators
This section discusses definitions and examples of key performance indicators (KPIs) relevant to the next-generation broadband network service – quality of service (QoS) that can be measured, modeled, and predicted over broadband networks by using AI technology.
KPIs are used to quantify the degree of excellence of a service. The actual measurement of QoS is a complex task, as service layers perform intricate calculations from bandwidth and packet loss to obtain QoS. Metrics considered basic for any service layer are throughput, delay, jitter, and loss. Telecommunication networks with different but integrated technologies transport a service or application from one user to another across multiple technologies. The ability to completely measure QoS in a network is limited due to practical constraints. Hence, indirect estimation relies on estimating QoS from measuring the network KPIs [8].
The equivalent KPI of no-blank video service layer QoS throughput is the same measure of the network available throughput. The network data throughput method can model QoS throughput in video applications. However, the long-term average throughput provided to the video client is lower than the actual throughput with packet drops at the application layer due to coded frames representing quality changed video received at the user terminal [2]. Such networks are called time-varying throughput networks, which makes modeling and prediction difficult. To make it simple, the same throughput model can be assumed for all segments.

5. AI-Driven QoS Enhancement Techniques

In the modern digital society, people expect a more mobile, smart, and high-quality life which means there is a growing demand for versatile and high-quality broadband access services among various potential users. With the rapid deployment of mobile networks, consumers are beginning to experience high-quality broadband services. However, the adequate capability and performance of the broadband access networks cannot be guaranteed as efficiently in the future. On the one hand, the explosion of wireless applications with unprecedented data usage growth and ultra-low latency requirement will require a near-pervasive utilization of wireless spectrum resource, thus posing a challenge of spectrum scarcity and spoiling the end-user QoS (Quality of Service) experience. On the other hand, new emergent applications with more stringent QoS requirement are blooming, which shall demand highly reliable ultra-low latency wireless access, thus imposing a great challenge to guarantee the end-user QoS. Thus, there is an urgent demand for next-generation broadband access networks with enhanced intelligent capacity and service quality guarantees.
Railways, as a key transport mode in the intelligent transportation system, have been exploding in the number of high-definition video surveillance systems for safety monitoring and incident detection. However, existing railway wireless access systems still face immense challenges in broadband access, coverage and resource utilization inefficiency, security and privacy, etc. Such challenges cannot be alleviated directly based on current information and communication technology architecture. For an emerging field, new scenarios and scenarios parameters might emerge and be integrated into existing knowledge representations. Thus, comprehensively and accurately understanding the scenarios and early warning of the possible risks is crucial for performance improvement and risk avoidance. As a result, machine learning, as a promising technology to map a feedforward model and simulate a complex system based on the data-driven paradigm, is witnessing its raising demands. First, machine learning can make use of the existing data representations of the system tool ecology to monitor the current state and performance of the system. Then, based on the trained understanding of the system, machine learning can be applied for control and regulation of the future action performances.
The expected broadband service enhancement is based on enhanced physical-layer techniques such as coordinated multi-point transmission and reception, which need to exploit the coordination of the mate access points based on an accurate user channel state information transfer via a mobile backhaul network with guaranteed throughput. However, as a distributed architecture, eGNBs in the cloud-ran or open ran architecture might be a low-capability transmission-reception node without centralising inter-node coordination functionalities. Although this issue can be compensated to some extent by the advanced AI-radios cooperation and Smart-RAN Intelligence Optimization technologies, it is still difficult to guarantee end-to-end QoS enhancement in Extract a component based on either global or learned cost.

5.1. Traffic Management and Optimization
In recent years, the increasing number of broadband subscribers has created an explosive growth of Internet traffic. To cope with this traffic growth, one of the key requirements for broadband service providers is optimal resource management. The algorithms and solutions need to be intelligent enough to autonomously react to the load situations in the network. In order to fulfil the requirements for SLA, a new architecture for automated operations and service delivery process is needed.
Good Quality of Service (QoS) is critical to the success of broadband service providers. Within the past few years, OTT players have significantly affected the bandwidth consumption and/or generated significantly more traffic than anticipated. Being off-net traffic, this has put increased pressure on the fixed and mobile broadband service providers. On one hand, they have to continuously respond to increased traffic demands from users wanting better video quality and faster

downloads. On the other hand, fierce competition among broadband service providers is forcing them to level off or even decrease the average revenue per user.

With the availability of huge amounts of data in telecom networks, machine learning (ML) techniques are gradually gaining interest in operation and business processes of broadband service providers. Traditional network management procedures based on static thresholds, deterministic rules and gut feelings of few highly skilled employees are being replaced by tickets driven by analysis of ML based findings. Continuous advancements in ML techniques, such as regression methods, Bayesian network classifiers, fuzzy logic algorithms, time-series forecasting, and artificial neural networks provide telecom operations with a wide variety of techniques to analyze historical, real-time and reference data and to learn from the resulting analysis. Several telecom best practices on onsite use of ML techniques have visibly improved efficiency and cost-effectiveness of operations and decision making.

The use of quantitative ML techniques is still very limited in the telecom industry and the focus is mainly on understanding model performance in conjunction with continued requirements. Tests in lab environments and clinical trials invariably took too long. Services enhance the lives of people fundamentally faster than infrastructures grow, and networks must significantly enhance models and facilitate actions in real time. Services in a broader sense involve all interactions with consumers and data, including informational, operational and relational scope. Network performance become an enabler of service positioning, delivery and consumption. Since performance of fixed and mobile broadband infrastructures is increasingly time-variant, notions of performance drift typically translate to potential quality of service drift. Quality of service improvement must be translated into network performance enhancement and resulting external factors improved, changed or added.

5.2. Dynamic Resource Allocation

Typically, broadband networks incur a heavy financial penalty simply by being aware of an incident [9]. Network monitoring must continue over time so as not to go backwards. The aforementioned approaches are ideal starting points, as AI/ML methods can contribute significantly to shaping the broad statistical picture of a network. Prioritizing the goals of wireless broadband networks, the study picks the 3GPP-defined 5G/NR scenario defined. Most high-level requirements already defined are set aside, as this investigation focuses on the specific categories of key performance indicators (KPIs) targeted. Second, transformations applied to the KPI data during pre-processing are summarized, and appropriate candidates for supervised learning are examined. Finally, performance evaluation measures relevant to time-series forecasting settings are summarized, as well as baseline algorithms to compare with the proposed regression networks. These have a direct impact on network performance after incidents and therefore high priority for automated monitoring. Without delving into RF specifics, KPI categories are chosen to hold maximum utility across operators and equipment manufacturers alike. Perhaps most importantly, the targeted domains must be curated such that any models created will generalize well when applied in the field. In that light, the chosen KPI categories span widely differing disciplines that are nevertheless inextricably connected. The first KPI category focuses on absolute user equipment (UE) performance, specifically physical downlink shared channel (PDSCH) throughput, a simple and well understood measure of the performance of a given active service. The second KPI category draws from network congestion measures, examining network resource utilization in relation to absolute load measures. Finally, the last KPI category monitors suboptimal network behavior in the form of application-layer performance measures, specifically user equipment (UE) service request delays.

5.3. Anomaly Detection and Prevention

Anomaly detection systems are vital for differentiating normal and abnormal activity patterns, which is crucial for the operation of telecommunication networks. In modern networks, high-velocity telemetrics are accumulated throughout the entire network in a distributed manner. The telemetrics used are typically VNF/state-related performance metrics, which unlike log messages, are structured and contain numeric performance parameters. Telemetry streams are high-velocity flows which require highly scalable and performant algorithms that can promptly detect and predict anomalies before their onset. Telemetry-derived performance anomalies have been actively researched using machine learning solutions, and numerous anomaly detection models capable of processing and analyzing telemetry data are available. However, these models are primarily developed using a single learning paradigm, limiting their recognition performance. With the rapid development of deep learning (DL)-based methodologies, more advanced DL-based models have been proposed, capable of detecting latent anomalies in complex systems and networks and outperforming conventional methods.

Equation 1: Z-Score for Statistical Anomaly Detection

$$z = \frac{x - \mu}{\sigma}$$

- x: Observed value
- μ: Mean of normal behavior
- σ: Standard deviation
- If $|z| > 3$, it's often considered an anomaly

Mobile edge computing (MEC)-based networks and an enhanced moving window-based data preprocessing framework are proposed to continuously generate a series of short calls categorized according to their cell identification for effective data creation in real scenarios. Two-phase multi-stage data-driven models built on a concurrent 1D-CNN-LSTM architecture are also designed to capture spatial and temporal information in analyzing network-wide user mobility. For improved model robustness, the proposed models are trained and evaluated with an enhanced attention mechanism. These models leverage spatial dependency and temporal dynamics as prior information of call mobility. Their anomaly events are consistent with the network architecture so that its knowledge can be successfully transferred to the designed detection models over diverse networks, and imbalance of data can be effectively alleviated with a frame-based transfer learning mechanism. A joint classification and regression-based frame-level transfer learning approach is proposed, to prevent and correct unwanted outcome biases of mitigating a data imbalance issue in network-wide anomaly detection tasks.
A framework for analyzing the suitability of a double-weighted ensemble consisting of unsupervised anomaly detection methods that utilize performance metrics for general purpose anomaly and attack detection in 5G RAN is described. The framework circles around a supervised classification model that utilizes the outputs from the unsupervised methods as features to be analyzed. Furthermore, a post-processing method for fine-tuning the parameters for the individual models of the ensemble, as a supplement to the framework, is also presented [11].

6. Case Studies of AI Implementation

This section describes three case studies where ANU developed predictive algorithms using the AI/ML framework for the management of communication and broadband networks [3]. The case studies considered following preliminary analyses to understand data formation, user behavioral analysis, clear definition of KPIs, reproducible baseline traffics, sensitivity analysis/stability conditions, and capture learning patterns.
• Study I: Enhancing ODN planning and management with AI-powered predictive algorithms: The main objective is to develop predictive algorithms using AI/ML techniques for reliable prediction of ODN ROF availability on a day-ahead time scale and to evaluate the benefit of dynamically upgrading ODN networks with the developed predictive algorithms with respect to a reference baseline ODN network upgrading strategy. The increasing penetration of bandwidth-hungry services, such as streaming services and AR/VR applications, has created the demand for high-capacity fibre-optic networks. This necessitates dramatic upgrades to the existing optical distribution network (ODN) to accommodate a new generation of equipment with a much higher reach performance. This study aims to develop predictive algorithms using AI/ML techniques that help network operators and government agencies ensure the reliability of operationally critical telecommunication networks by capturing highly influential regional factors in a nodes clustered approach for day-ahead prediction of free hours with no incoming radio-on-fibre demand in ODN.
• Study II: SLE-FIS: A framework toward an AI-driven SLE in broadband networks: The primary purpose is to provide an AI/ML framework to integrate different types of data-driven technologies to achieve intelligent SLE functionality with AI predictively. Intensive ML-related research is proposed to achieve the vision of intelligent broadband networks where AI adoption is ubiquitous. Legacy networks equipped with traditional equipment cannot cope with the increasing traffic demand by upcoming applications and services requiring network elasticity and programmability. To achieve this vision, an intelligent SLE is required to monitor and assure delivery quality by intelligently learning about network and service conditions using machine-learning techniques' predictive capabilities.
• Study III: AI-driven predictive SLA negotiation for broadband services: The primary objective is to identify the state-of-the-art in AI application opportunities for predictive SLA negotiations, identify critical research gaps and challenges, and evaluate potential approaches for addressing these challenges. A promising approach for predictive SLA negotiations based on deep reinforcement learning that combines multi-head attention mechanism self-learning and graph neural networks with an unsupervised pretraining and supervised fine-tuning scheme is proposed to contribute toward achieving this vision. The analyzed case study illustrated that this approach can increase stakeholder satisfaction while decreasing the number of callbacks for SLA violations. The flexibility allows for its tuning to a variety of applications and service domains, including telecommunications, IoT platforms, and cloud service providers.

6.1. Successful Deployments in Major Networks

Artificial intelligence (AI) has evolved to a stage where it can provide computational solutions to problems that have previously been analyzed. AI technologies have undergone changes that have led to the expansion of their applications and use. In part, such changes have been driven by deep learning (DL), a subset of AI that resulted in an unforeseen excellence of its results in many areas previously claimed by mathematics, statistics, or field-specific expertise [3]. As a result, there is enthusiastic effort and investment in applying AI—including real-time, automated, sometimes autonomous solutions—to a diversity of fields where their complementary capabilities could provide an advantage over traditional approaches. This role of AI is not specific to broadband networks but holds for all different associated infrastructures.

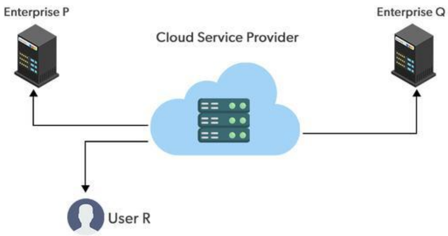

Fig 3: Cloud Deployment Models

Improvements to the infrastructure itself have also been developed and deployed to deal with challenges posed by the sharp growth in broadband consumption. Optical fiber is a case in point as it has replaced or augmented legacy access media but is also reaching maturity and has limits in distance and extensivity. AI models have been applied to improve the optical resource allocation, wavelength routing and assignment, or on-the-fly origination of Wavelength-dated Optical Packet Switching, and are also approaching maturity and competition with traditional metrics. AI is in fact already being deployed for real-time analytics in the operational control layer of major broadband networks with the role of expediting network fault detection and service restoration in practice, as this is currently a time-consuming activity.

More generally, the ongoing collection of very large amounts of real-time application data has already supported the development of fast heuristics that could be implemented to improve network topology analytics. The ongoing availability of general computing resources and development of methods that could be adapted to suit network topology optimization makes it likely that true AI-manipulated topologies could be engineered into the future. Several research efforts have treated the deployment of AI-enabled solutions in broadband networks using real-world data and developing models that operate in a hybrid fashion, taking advantage of both AI and traditional methods.

6.2. Lessons Learned from Failures

This section discusses the major lessons learned after failures in deploying some AI-based use cases in live 24/7 production mode. The models were initially tested and verified in preparation mode with post processing runs against a larger data set. Even with extensive pre-checking and simulation runs, some unintended consequences came as a surprise once the revamped models went live with the current data and operating conditions. This section outlines these issues and how they were resolved to make sure they do not happen again in the future.

After the machine learning models to detect suspicious activities were put into production, steep increases in the volume of alerts arose. It took a few weeks to discover the origin of the problem: the randomly selected set of training records included an unusual spike in the number of alerts for spam records. As a consequence, a huge backlog of unresolved alerts for suspected spam results occurred. Most of the new suspicious activity alerts were quickly resolved, but the flood of potential spam alerts overwhelmed the operators. Once it was recognized internally as the problem source, training on a better set of records could be prepared. Three countermeasures were taken to avoid a repeat occurrence in the future: (1) routinely maintain restraints on the records selected for training, preferably at least in partnership with the data quality group to check train record quality; (2) check the training record set immediately after selection; and (3) sample alerts on a new selected record set and verify that the generated models do not generate an unusual volume of new alerts [12].

After these issues with the spam detection use case were resolved, machines began to learn how to detect large scale spammers development. New systems were quickly deployed to model the production environment, including test watches gathered from previous spam events. Although some small adjustments were necessary with regard to local time zones, all issues were resolved with limited involvement from the development team. Again, operators took on responsibility for monitoring the new watch detection alerting set. After fine tuning different alert parameters, the issued alerts decreased to an acceptable number and could be dealt with promptly, and the continued watching was made to avoid alert floods by options for machines learning and proactive monitoring activities.

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7. Challenges and Limitations

Ensuring that 6G-enabled use cases that have drastically different requirements can coexist in next-generation networks, while providing quality of service (QoS) guarantees for each user as per its slice is a challenging task. Slicing and O-RAN architecture can help mitigate this challenge to a certain extent. Nevertheless, the slice-level resource allocation problem, especially in a dynamic environment, is itself an NP-hard problem. Furthermore, the general structure of AI techniques misbehave in such challenging dynamic environments, leading to high convergence times. This would make traditional AI techniques infeasible for 6G use cases. Proposing a novel agent architecture built on DQN that achieves state-of-the-art resource allocation performance while minimizing the convergence time in a dynamic environment is a fundamental step toward operationalizing agent-based resource allocation. Moreover, equipping agents with methods or knowledge sources that help meet the requirements of QoS-sensitive services without affecting other high KPIs is critical. Lastly, resource allocation in beyond 5G networks is a multi-agent approach in which multiple slices share network resources and other AI-based solutions [9].
As of now, two key issues regarding AI-enabled networks have been thoroughly researched; However, despite this rapid research growth in AI-enabled networks, there are still many open issues yet to be addressed. The issues: the life cycle of AI-based solutions where requirements need to be monitored and fed back into the AI solution together with new training episodes and network states; at which point in the ongoing dataset the AI solution should start its retraining phase has not been researched comprehensively and needs to be addressed comprehensively such that maximization of rewards is maintained during retraining. Although the idea of monitoring the environment and feeding back a change in a pre-trained AI-based solution together with new training episodes is not a novel concept [3]. It still needs to be thoroughly researched to provide implementations of how this can be performed in AI-enabled networks with concrete research directions and challenges corresponding to it.

7.1. Data Privacy and Security Concerns

Data privacy and security concerns are raised with the ubiquitous use of advanced technologies in broadband networks. Increasing functionality leads to more personal data transmission in emerging technologies such as AI, IoT, big data, and blockchain. Security concerns: unlike other network types since their users are critical, any occurrence in marine broadband networks can severely impact an entire maritime area and society as a whole. Thus, data security is crucial for Marine broadband technologies, as they process and connect the ship with various sensitive applications. To satisfy this requirement, network isolation issues must be solved. Isolation will result in a completely closed system where AP must describe all users requesting it. This may raise practical deployment issues since essential data packets to be transmitted by the ship may also be missed. Thus, any data isolation on the data level is not practically feasible as such network type will not exist anymore.

Equation 2: Data Sensitivity Exposure Score (DSES)

$$DSES = \sum_{i=1}^{n} V_i \cdot S_i \cdot E_i$$

- V_i: Vulnerability score of data component i
- S_i: Sensitivity level (e.g., PII, financial, etc.)
- E_i: Exposure probability (likelihood of being accessed/breached)
- Higher DSES = greater privacy/security concern

Developing AI-driven solutions for process automation face various challenges, such as training ML-based algorithms on sensitive information. Transferring sensitive information to the training server may expose enterprises to security risks and increase training costs due to huge memory demand and long convergence. Additionally, the popularity of deep learning has made it possible for attackers to train DNNs to imitate the outputs of a target DNN model based on query results. Model stealing will impact the revenue of the model owner. These risks have led to great concerns from governments, organizations, and users regarding the security and privacy of AI-driven systems. Thus, there is an urgency to strengthen the security of AI-driven systems and algorithms [14].
Data communication security has been widely exploited, and various schemes have been proposed, but they can hardly satisfy all aspects of edge-computing-based AI systems. Encrypted data can be processed by the ciphertext-processed model due to the limitation of the homomorphism encryption scheme. Only limited operations can be designed to process encrypted data, compromising model prediction accuracy. Instead of getting the accurate answer, an incorrect answer must be returned for safety. Additionally, the operation of increasing the data dimension is designed, which enlarges the operation error of the DNN model.

7.2. Integration with Legacy Systems

Despite the anticipated initial performance gains that AI Network Management strategies may provide, it must be understood that – at this stage of proliferating AI applications in telecommunications – there must still be a strong emphasis on ensuring that network management will continue to function effectively while "learning" takes place. The "learning to learn" concept suggests the possibility of rapidly assimilating knowledge gained previously across many operators' networks and companies sophisticated enough to manage gainful, full return from such considerable investments.

Equation 3: Integration Compatibility Index (ICI)

$$ICI = \frac{\sum_{i=1}^{n} C_i \cdot W_i}{\sum_{i=1}^{n} W_i}$$

- C_i: Compatibility score (0 to 1) for component i
- W_i: Weight (importance) of component i
- n: Number of legacy system components
- Higher ICI means better compatibility with legacy systems

As mentioned previously, some firms are already registering advantages with respect to performance and efficiencies from a competitive set of AI-based management solutions. However, others are already running the risk of falling behind, creating a potentially explosive convergence path as AI Network Management becomes both mainstream and the state of the art for telecom networks. Competing against a moving benchmark inevitably poses difficulties, and solutions already in operation may need to be traded against other infrastructure platforms. This introduces yet more complexity in terms of Systems Engineering (SE) cost benefit evaluations, so insight into the degree to which AI will need to integrate with existing Operations & Management (O&M) process steps and network solutions is crucial [3]. Currently, networks have still to progress from "learning about learning" to "learning to learn" AI-based capabilities. This stage of a ten-year new network generation cycle at commercial launch typically sees demand for capacity or performance improvements. Preceding generations have determined a dual framework of high-level functional grouping, the resource-dependent plan-build-operate performance and capacity dimensions of communications networks. The Dawkins model suggests an iterative sequence of specifying repeatable tasks in the first stage on the creative frontiers of virtual networks, VSLs optimal on build variables such as machine-size and bit-rate, plus cumulative increases in across networks. Sequentially, researching and developing these solutions into technical capabilities as operationalized resources will require addressing and operationalizing multiple building block technologies across multiple generic system, platform, and functionality levels for integration across engineering domains.

7.3. Scalability Issues

Despite the advantages of leveraging AI for QoS monitoring and anomaly detection, a few critical challenges need to be addressed before applying this technology for the next-generation fixed broadband networks and services. Those challenges include the need for adequate data for training, validation and testing; the need to integrate different AI technologies; the difficulty of interpreting AI-based decisions; and the complex networks and circumstances in an automated approach.

To address the challenge related to the need for sufficient data for training, validating, and testing the AI models on the available types of data, it is proposed to work with different data types, data sources, and techniques, so that the decision space can be maximally explored by the AI model for better performance and generalizability. Sufficient data types, structures, and processes related to QoS in diverse networks/services should be first identified to cover the anticipated theoretical scenarios in an AI-based modelling approach. For a QoS evaluation service level agreement, both the target definition and corresponding metrics should be clear enough before collecting data from diverse sources that explicitly exemplify the status of these metrics in an agreed temporal and spatial context.

The challenge of integrating different AI models/technologies is expected to be more critical and difficult than the data challenge. The heterogeneity of data types and structures for modelling QoS at different abstraction levels leads to different AI technologies and models that capture different QoS behaviour of the networks/services. However, the common goal is to combine these different AI models into a single entity that can generalize the diverse QoS behaviours by capturing the inter-relationships instead of aggregating on arbitrary QoS metrics. There are also opportunities to unify the modelling for different subtasks of interest. For instance, the awareness of QoS is expected to be complementary but not independent. The knowledge of different wireless networks and services learned by the universal model for efficient exploration can benefit the network/service model for an easy approach for unlearned scenarios thanks to the structured commonalities. Multi-task and meta-learning are potential approaches to be explored for developing the integrated modelling and learning processes.

Aside from the interpretable AI challenge, many difficulties and limitations await exploration from several aspects. For AI to be aligned with these networks/services, their operational principles, designs, and performance objectives should be made available so that the exploited model states and rules can be cross-referenced. Such information, however, may not be available because either it is still being clarified and standardised or it will evolve constantly with the development of the networks/services, which alongside their complex interconnections, traffic patterns, and the generated, attracted behaviours, presents challenges for safely and reasonably studying and utilising AI-based inferences. To address these challenges, the established AI expertise to discover and investigate solvable models should be trained from scratch by imitating the instructions of existing networks/services in the standardisation frameworks with increasing complexity until being allowed to conduct investigations independently.

8. Future Directions of AI in Broadband Networks

To consistently deliver desired Quality of Service (QoS) in next-generation Broadband networks, the communication between different network components should be both Proactive and Predictive. To realize proactive and predictive communication in these networks, the latency of the information exchange need to be reduced to few milliseconds (ms), which is not straightforward with the current compute and transport capabilities of network components and their configuration. However, machine learning mechanisms such as Reinforcement Learning (RL) can provide automation to network tasks such as dynamic reconfiguration, failure recovery, scan detection etc.

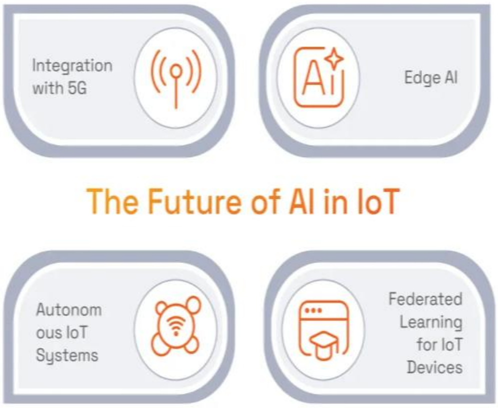

Fig 4: SPD Technology

In particular, an RL agent(s) can reside at the IP-routers for monitoring and detection of any subtle changes to the conformance of parameters such as latency, packet-drop etc. Anomaly detection is a non-trivial network monitoring challenge often approached by heuristics/empirical methods for corrective action. With the proper stratification of distributed RL agents at the routers with peer-to-peer communication channels, the aberrations in QoS parameters can be captured, escalated and resolved in sub ms communication intervals. Consequently, with the knowledge about performance aberrations, probable root-cause(s) of the problem can be obtained from the RL reward-mapping cues thereby improving MTTR. These measures can enhance end-user satisfaction by guaranteeing proven QoS and avoiding revenue penalties levied by regulatory authorities in case of unfulfilled SLA.

Furthermore, Self Organized Networks (SON) protocol standardization and its deployment as a result of commercial expansion of cellular technology providers has created a sizeable market for engineering next generation of SONs. Traditional SON schemes are primarily based on heuristics which limits their performance adaptivity. Therefore, an additional layer of ML can be added to SON schemes for improvised run-time performance. Efforts in this direction can advance network awareness and intelligence, yield resilience to disruption attacks or catastrophic failure, minimize inter-layer cross-talk and conflicts, enhance QoS, and support smooth operator migration to self-management. Finally, novel access networks, such as millimeter-wave (mmWave) and terahertz (THz) band, require advances in Mesh Networking with emphasis on to efficiently keep a conformance of QoS over a wide area in diverse scenarios such as mobile crowd-sourcing. Here again, novel ML algorithms can be key enablers.

8.1. Emerging Technologies and Innovations

The unprecedented demand for high data rate and quality multimedia services has led the Next Generation Networks (NGNs) architecture and technology evolution from passive transport systems to active service-oriented systems. The network should accommodate various types of services with different Quality-of-Service (QoS) parameters and associated levels, adaptively supporting Quality-of-Experience (QoE) monitoring and enhancement. At the same time, considerable attention must be paid to maintaining the service continuity across generations of networks and their domains. All of these imply a fundamentally different service assurance approach to QoS/QoE provisioning, monitoring, and enhancement in comparison with the currently predominantly used one.

The convergence of Artificial Intelligence and telecommunications has brought a revolution to the development of intelligent networks. Artificial Intelligence (AI) automates the analysis and connection of large amounts of information and data to help identify trends and solutions. AI has a great potential to improve the quality of service and end-user satisfaction in wide-ranging industries, including telecommunications, media, and entertainment. Telecommunications have an extensive scope in the optimization of respective networks and services through AI. Thus, bridging several research fields together, including telecommunications, AI, telecommunications, and media service quality. AI-enabled Intelligent Service Assurance as an end-to-end analysis platform and necessary auxiliary tool for comprehensive examination of services in 5G-6G networks and optimization of their assurance. Deep-learning-based service representation and identification regarding conversation, networks and services, service taxonomy assessment and enhancement. Machine learning-guided design of QoS & QoE monitoring solutions and assurance frameworks instruction set to application developers and networks staff.

8.2. Potential Impact on Industry Standards

In June 2022, the 3rd Generation Partnership Project (3GPP) completed Release 17 of 5G cellular networks. 5G networks map out a rich set of technical advancements in the capacity of spectrum usage, energy efficiency, reliability, latency, and connection density [16]. Artificial intelligence (AI), machine learning (ML), and data-driven techniques are regarded as a key feature of 5G-Advanced and sixth generation (6G) networks. AI is expected to help manage, design, optimize, and predict network performance proactively based on big data analysis to improve the quality of service (QoS) perceived by mobile users. Many telecommunication and computing industries have started to work on integrating AI capabilities into next-generation communication networks. AI-enabled radio access networks (RANs) involving two topics: Radio resource allocation in AI-enabled RANs and AI-enhanced wireless network performance analysis were investigated in Release 17. A new study item (SI) on AI-native air interface was proposed in Release 18, focusing on integrating AI into the air interface. This study item aims to explore not only performance improvement but also complexity reduction. A target was set to assess the performance of the AI-native air interface compared with conventional methods. Moreover, a common architecture and common interfaces for AI-enabled feature selection of an air interface in a wireless communication system was to be established.

A use-case-driven approach is employed to select representative use cases for better addressing the major challenges. Among these use cases, channel state information (CSI) feedback enhancement was selected to be studied in great detail. AI for CSI feedback enhancement aims to improve the performance of CSI feedback in massive multiple-input and multiple-output (MIMO) systems. Precoding and a large number of antennas at the base stations (BSs) make the acquisition of coherent CSI units to be fed back from UEs to BSs a bottleneck to maximize the benefits of massive MIMO [3]. The tremendous overhead caused by the increased number of feedback bits can be suffocated by developing a new paradigm for the feedback module. It is proposed to automate the compression and reconstruction of the CSI by AI and mapping the CSI to index codewords without explicit features. It is demonstrated that the index shows more robustness and better reconstruction accuracy of the CSI than other AI-enhanced algorithms.

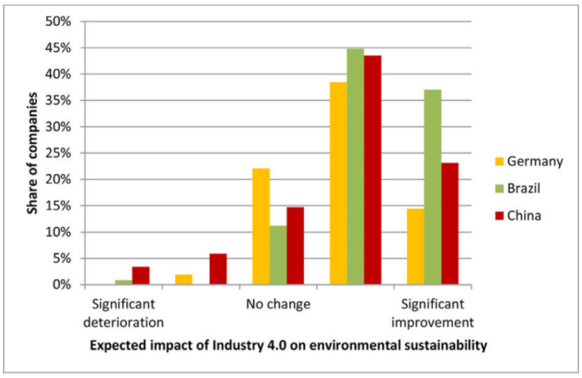

Fig: Expected impact of Industry 4.0 on environmental sustainability

9. Policy and Regulatory Considerations

The connections between AI, innovation policy, and regulation are multifaceted and complex. AI is arguably the most strategic technology – given its potential to enable disruptive innovation that transforms socioeconomic and political systems – in which countries will seek to build their own future-leading indigenous capabilities. There will be a requisite policy discussion around the value chain and whether this is product development or pre-training (and data sovereignty) → major allegiance issues globally in which technologists will need to lobby to ensure that homegrown innovators get a preference. National security in terms of economic, tech, and cyber will need serious consideration given current events, and a government maturity analysis will need to be undertaken to understand the implications of either being states with wide capabilities or narrow capabilities with significant barriers to entry for would-be incumbents in particular applications [2]. More generally, it will be necessary to consider where to focus effort: deploying existing capabilities, keeping pace with ‘leaders’, becoming ‘best in class’, contributing to the cutting edge, or being seen as a major global player. It will be necessary to consider whether to adopt an industry sector or vertical approach, or whether to concentrate on high-level regulatory issues: technical standards are notoriously difficult to influence but are vital. Encompassing fundamental rights and public interest considerations, it will be necessary to consider how to prevent or mitigate harms to individuals and society from the application of AI. This discussion will need to mark the limits of the existing Human-centric AI discussion generally too focused on explanation, transparency, and interpretation based on compliance with rules. It is essential to provide high-level analysis and advice, rather than strategies, on the entire class of national measures taken or contemplated by jurisdictions. Potential areas in which to focus effort: classification by measure (outlaws, obligations, etc); by AI applications (how to improve); analysis of existing/ongoing transnational cooperation and other means of addressing non-sovereign jurisdictions; etc. Socio-systems analysis of strengthened, but ultimately "silent", filter-bubbles that displace trust in existing information systems, and dedicated applications to AI model synthesis and toolbox. These will only be completed in whiter spaces, of policy level "as opposed to technology, market or economic" roundtables.

9.1. Regulatory Frameworks for AI in Telecommunications

The telecommunication services provided by national and international networks are governed by various regulations and guidelines to promote the wider interests of the society. This includes licensing, construction of infrastructure, competition in the provision of services, pricing, technology neutrality, and transparency in the standards and protocols used. The regulatory environment is evolving worldwide since the introduction of Artificial Intelligence (AI) across domains enabling faster decision making, automatic operation and management, and unlocking long-pending opportunities. The use of AI in the mobile telecommunications industry can help network operators in network planning, assurance, maintenance, and security. In addition, AI can be leveraged for scenarios like low-orbit satellites, packet microwave, and mobile edge computing. However, with the news of AI-related incidents at major corporations, the AI regulatory landscape is also evolving quickly.

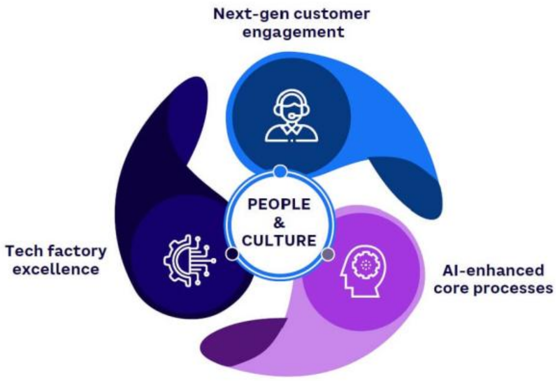

Fig 5: The AI-amplified telco

To get insight into the telecom regulation for AI, the AI regulatory landscape forms the basis. In many countries worldwide, Ministries, Departments, and Agencies are motivating and supporting the proliferation of AI innovation across sectors. Regulators with connection to telecommunications who were active in the AI conversation include various national and international bodies. The Telecommunications Regulatory Authority of India is working closely with other ministries in preparing the national policy for AI. Technology-neutral and regulation-agnostic approaches have been considered for AI as well.

A selective summary of guidelines in AI regulations from telecom regulators shows that most of them recommend the establishment of surveillance and auditing frameworks, processing fairness, battles against misinformation, promoting human well-being, and minimization of harms and bias. Policy enforcement considerations include a showcase of best practices, efficient and proportional regulation, ethics and transparency, limitation of costs and obligations alongside reasonable expectations towards businesses. These findings are in addition to the prominence of open dialogue, co-regulation, and research-based regulation approaches found extensively in the AI regulatory landscape. The AI regulation approach is yet to soften, evolve, and mature in the telecom regulation landscape with moving focus from technology-neutrality towards sector-specificity.

9.2. Balancing Innovation and Consumer Protection

The ultimate goal of any networking and telecommunication implementation is the satisfaction of customers and users. This is absolutely true for any development of telecommunication technologies and systems, which are justified when contributing to improvement of life, quality of service, productivity, and economics. The same reasoning is valid in the case of networks operating in a strictly commercial environment, but holding extreme importance for social life and business in a globalizing economy [2]. The ultimate goal of optimization techniques at the network and application layer is to ensure End-user perceived QoS. Although existing QoS optimization and enhancement techniques are bottom-up, additional knowledge and information about content, user Information Technology (IT), and applications bring unprecedented opportunities for optimizing quality on NGN and at service provision level.

In the interactive networked multimedia environment, more than one or two sides of interactions between users and applications can conceivably participate in providing QoS. Intelligence can be introduced in conditions processing during run-time, on threshold base separating conditions for two types of processing. New conditions can be tested by the user, the application, or the network, shaping the fRC policy by different entities. Whatever entities process fRC policies, the End-to-End (E2E) QoS credibility is needed as it impacts users' and applicants' satisfaction. Scenarios for demonstrating theoretical analysis have been developed. A framework for modelling the end-user perception of QoS in an IMS-enabled NGN multimedia network is proposed. The perception is thought off as QoE's quality awareness. A service aware policy-based approach to NGN quality assurance is presented, taking into account both perceptual quality of experience and technology-dependant quality of service issues. Along with technology-oriented performance measures, passive monitoring of perception modelling, knowledge-based processing, and end-user controllability are taken into account to enable effective support for users' requests, applications preferred quality, and at the same time QoS maintenance by networks.

10. Conclusion

Over the past several years, various telecommunications researchers and engineers have pursued an active research agenda to address ways to more efficiently and effectively support Internet-based services based on a national and global network of high-bandwidth, general-purpose arteries. This brain function efforts have been combined with brainstorming and recruiting efforts to suggest novel visions for what future large-scale systems may contain and what paradigms underlying their functionality may yield significant new capabilities and/or service options. Key elements of the overall proposal are based on a view of the overall telecommunications vision as consisting of five interacting layers. The Core Control Layer is a top interruptive guide layer consisting of the Core Quality Networks. The Core Quality Networks are based on the notion that the quality of service requirements of various classes of transport needs differing segregated and isolated classes of high-speed transports. Each core quality network transports data under core transport protocols involving mechanisms for collecting client QoS transport metrics and for affecting varying degrees of prowess over pending completion times and pathological event rates. The Service Layer sits above the core quality networks, and involves a set of service integration mechanisms which take input from application layers, delimit streams of data from these inputs into multiple flows as defined by their QoS requirements, and map the flows onto core quality networks. Lower layers consist of various local access networks and connectivity devices which connect end users to the core quality networks. Here the local access networks may be of a multitude of types and of different provision levels as well. For example, a network architecture may have two access types one being fiber optic with fiber taps run to homes and businesses serviced by a few high Specification active ports deployed throughout linear interconnections, and another cellular access network. The local access networks may use the core transport protocols in the same way that the Core QoS Networks do, or they may employ a different scheme albeit with functionality that dramatically mimics their purpose and applicability. Local QoS Networks then take over and derive new local active ports and fiber taps necessary to satisfy expanded service demands.

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